UNIVERSIDADE TÉCNICA DE LISBOA
INSTITUTO SUPERIOR DE ECONOMIA E GESTÃO

DOUTORAMENTO EM ECONOMIA

# FLIGHT-TO-QUALITY PHENOMENON AS A SOURCE OF FINANCIAL INSTABILITY

Mariya Gubareva

**Orientação:** Professora Doutora Maria Rosa Vidigal Tavares da Cruz Quartin Borges

**Presidente do Júri:**

Reitor da Universidade Técnica de Lisboa

**Vogais:**

- Doutor João Alberto de Sousa Andrade, professor catedrático da Faculdade de Economia da Universidade de Coimbra

- Doutor Efigénio da Luz Rebelo, professor catedrático da Faculdade de Economia da Universidade do Algarve

- Doutor José Paulo Afonso Esperança, professor catedrático do ISCTE – Instituto Universitário de Lisboa

- Doutor Carlos Alberto Pestana Barros, professor associado do Instituto Superior de Economia e Gestão da Universidade Técnica de Lisboa

- Doutora Maria Rosa Vidigal Tavares da Cruz Quartin Borges, professora auxiliar do Instituto de Economia e Gestão da Universidade Técnica de Lisboa

2013

*To Dmitri*

*Do not seek for unity in the whole, but rather in the uniformity of distinction.*

Kozma Prutkov

# Acknowledgments

I would like to thank Prof. Dr. Maria Rosa Borges for her supervision during this project and thesis preparation.

I would also like to thank, for their comments:

- the Coordinator of the Ph.D. Program in Economics Prof. Dr. Miguel St. Aubyn

and participants at:

- Doctoral Seminars organized by Economics Department and Research Unit of Complexity and Economics (UECE) of ISEG, School of Economics and Management;
- 6th Ph.D. School of Globelics Academy, ISEG, Lisbon, Portugal, 2009;
- 1st World Finance Conference 2010, Viana de Castelo, Portugal, 2010;
- 7th International Conference on Advances in Applied Financial Economics, Samos, Greece, 2010;
- 1st International Conference of the Financial Engineering and Banking Society, Crete, Greece, 2011;

I also thank the School of Economics and Management (ISEG) and the Rector´s office of UTL for the partial financial support of the Samos conference expenses.

I am thankful to the Fundação para a Ciência e a Tecnologia (FCT) and the European Social Fund under the Programa Operacional Potencial Humano of QREN Portugal 2007-2013 (POPH/FSE) for financing this project by means of the individual doctoral grant SFRH/BD/71555/2010.

# Abstract

A general theoretical framework is proposed to analyse Flight-to-Quality events, defined as a mass investment migration from risky to safe assets. The model consists of only two asset classes, risky and safe. The framework is applied to Flights-to-Quality from emerging market public debt to U.S. treasuries, in the period 1998-2010. An alarm signal system is designed to warn of upcoming Flights-to-Quality and their terminations, and is applied: (i) to delimiting hypothetical Flights-to-Quality on an ex-ante basis, which are compared with historically observed episodes, to test the quality of the alarm signals; (ii) to elaborate dynamic interest rate risk hedge strategies, characterized by higher returns and lower volatility in comparison with statically hedged investments. The proposed framework potentially allows for improving the timeliness of financial policies, which can be triggered by the alarm signals. It can also be a useful tool for defining adequate policies to be implemented acting either on an insufficient supply of the safe assets or on a decreasing demand for the risky investments, thus contributing to a more stable economic environment.

**Key words**: Flight-to-Quality, financial crisis, asset appetite metrics, emerging market debt, U.S. treasury bonds, interest rate risk, dynamic hedge strategy, financial policies.

# Resumo

Propõe-se uma abordagem teórica para análise de eventos *Flight-to-Quality*, definidos como a migração em massa de investimentos em, activos com risco para investimentos em activos sem risco. O modelo considera apenas dois tipos de activos, com e sem risco. A abordagem é aplicada a eventos *Flight-to-Quality* da dívida pública de mercados emergentes para dívida pública norte-americana, no período 1998-2010. É desenhado um sistema de sinais de alerta para emitir sinais de aviso relativos ao início e ao término dos eventos *Flight-to-Quality*, o qual é utilizado para: (*i*) a identificação *ex-ante* (hipotética) dos eventos, os quais são comparados com os eventos históricos observados, para testar a qualidade dos sinais gerados; (*ii*) para elaborar estratégias dinâmicas de cobertura de risco da taxa de juro, que asseguram rendimentos mais elevados e menor volatilidade que estratégias de cobertura de risco estáticas. A abordagem proposta permite melhorar o tempo de resposta das políticas financeiras, as quais podem ser despoletadas pelos sinais de alarme. E pode também ser um instrumento útil para a definição de políticas, seja para correcção de uma oferta insuficiente de activos sem risco ou de uma procura insuficiente pelos activos com risco, contribuindo assim para um ambiente económico mais estável.

**Palavras-chave**: eventos *Flight-to-Quality*, crise financeira, métrica do apetite por activos, dívida pública mercados emergentes, dívida pública norte-americana, risco de taxa de juro, estratégia dinâmica de cobertura, políticas financeiras.

# Table of Contents

# List of Tables

# List of Figures

# 1. Introduction

The Flight-to-Quality phenomenon has attracted considerable attention from academic researchers and market practitioners in their attempts to comprehend the sources of financial instability, see, for example, Diamond and Dybvig (1983), Caballero and Kurlat (2008), Beber et al. (2009), Gubareva (2010), and Inci at al. (2011), among others. This phenomenon is usually referred to as a mass investment migration from risky assets to safe financial instruments, for example, U.S. Treasury bonds, leading to a growth in their prices and a decrease in prices of relatively unsafe instruments.

Many mechanisms have been proposed to explain Flights-to-Quality and employed in models targeting a better comprehension of their dynamics. These models are based on: rising price volatility and overall risk aversion (Vayanos (2004)), financial intermediation modeling (He and Krishnamurthy (2008)), tightening of margin requirements by regulators (Brunnermeier and Pedersen (2009)), pricing power of predominant players and their predatory behavior (Brunnermeier and Pedersen (2005)), and Knightian uncertainty which causes wide spreads between bid and ask prices (Caballero and Krishnamurthy (2008)), among others.

This research focuses on the asset appetite metrics applicable to Flights-to-Quality in general while special attention is paid to the Flights-to-Quality out of Emerging Markets' fixed income securities towards U.S. Treasury bonds. A systematic description of the more than hundred events is performed over the period 1998 – 2010. The Alarm Signal System, based on the proposed asset appetite metrics, aimed at delimiting Flights-to-Quality on an *ex-ante* basis is developed. The approach applied here allows for constructing a system of early warnings of upcoming events and of their terminations, which could be used for portfolio hedge and as a support for the governments´ timely policies aspiring to improve financial stability.

In spite of the vast research conducted on Flight-to-Quality events, there seems to be a certain shortage in literature regarding quantitative predictability of crises forecasting their ignitions through the Flight-to-Quality analyses.

Additionally, there exists a lack of methodologies regarding the predictability of these events. This can be explained by considering the following two reasons. The first is related to the fact that Flights-to-Quality tend to be triggered by unanticipated and unprecedented factors. Thus, many commonly used prediction techniques based on linear and polynomial regressions, correlation analyses, etc., seem to be of limited usefulness. The second explanation can be ascribed to the research situation in this field where many scientific works are focused on the description and modeling of the Flight-to-Quality event itself within its time window. However this draws the research community's attention away from a thorough understanding of what happens prior to these events from economical and financial points of view.

The present research seeks to contribute to the investigation of Flight-to-Quality, as there is a relatively little literature examining timeliness and possible alerts of these phenomena. Filling this gap, the present work describes the development of the Alarm Signal System and its application to engineering of diverse dynamic hedge models. Finally, the discussion of financial policies focused on how to withstand Flight-to-Quality impacts on the real economy is addressed from the point of view of supply-demand misbalance in respect to both the safe and the risky assets, representing an advance in this issue of growing importance.

The overall intention of the present research is to shed light on the processes originating Flight-to-Quality events, envisaging better comprehension of the resulting financial instability and focusing on the possibility of forecasting these phenomena. In order to achieve this general target, the following research objectives serve as milestones of this work.

The first objective is to deepen the comprehension of the nature of Flight-to-Quality events, and develop their typology. With this purpose the identification algorithm is to be developed in order to select the events of interest for further analysis. Special attention is paid to the adequacy of the data selection, ensuring it is the correct choice of the fixed income indexes to describe both the safe and risky asset classes in order to allow for diagnostics of the inverse changes in their performances when the safe assets outperform the risky debt issues. As the Flights-to-Quality do not exhibit standardized durations, each index performance has to be measured over diverse widths of the analyzed window for each of the dates from the 1998 – 2010 analyzed interval. So, to diagnose an inversion in the performance of the two indexes becomes a serious task in itself and is to be appropriately addressed through the development of the automated numerical approach.

The second objective is to set up a model, which can provide insights to the origins of Flights-to-Quality. The concept of the sectoral shifts within the economy and, hence, within the investment universe is to be applied to modeling the pre-Flight-to-Quality and Flight-to-Quality dynamics of investment flows. The performance of the sectors of the fixed income investment universe is described by the same fixed income indexes used for the *ex-post* identification of Flights-to-Quality. The next step is to quantify the investors´ attitude towards reallocation of their investments.

The third goal is dedicated to the proposition of specific metrics to gauge the investors´ willingness to hold either safe or risky assets, or to measure their interest to invest in fixed income securities as a whole, i.e. their aggregate appetite to hold both risky and safe assets. These three asset appetite metrics, for risky, safe, and cumulative appetites, are derived from the respective index performances using two special procedures, developed for this purpose, namely, the correction for the influence of the risk-free interest rate changes, and the adjustment of the indexes′ returns to the same level of expected riskiness. These metrics are to be used as a base of the Alarm Signal System to warn of upcoming Flights-to-Quality and their following terminations. It is worth noting that the latter represents an advance beyond the current state of art, as the problem of Flight-to-Quality termination is not usually addressed in the literature.

The forth aim of this work is to develop a proper Alarm Signal System, based on the specific asset appetite metrics. Then its efficiency in delimiting Flights-to-Quality events on *ex-ante* basis is to be assessed. With this intent the developed Alarm Signal System is applied to generate the entry and exit alarm signals, delimiting the start and termination dates of Flights-to-Quality, based only on the information available prior to the date of the respective alarm signal generation. The strengths and durations of the Flights-to-Quality delimited by this Alarm Signal System are then compared to those of the respective Flight-to-Quality occurrences as identified on *ex-post* basis by means of the total return-based automated numerical approach, i.e. using the information from the dates both preceding and succeeding those events.

The fifth and final goal of this research is to propose and test diverse dynamic hedge strategies in order to mitigate effects of downside risks related to Flight-to-Quality events and reduce volatility of returns. These hedge strategies are to be based on the outputs of the Alarm Signal System, i.e., the alarms, which indicate the dates of the dynamic switching in the allocation of the portfolio assets and liabilities. Additionally, an applicability of the Alarm Signal System to the elaboration of financial policies is addressed. It is expected that the proposed approach could improve timeliness of financial policies and result in efficient hedges of an interest rate risk of investment portfolios.

The main body of the Thesis consists of three Chapters. The first provides a survey of the literature related, among other matters, to the historic evolution of the risk concepts and perceptions. Special attention is paid to the Flight-to-Quality phenomena and crisis situation analyses.

The second Chapter, dedicated to the Flight-to-Quality model analysis, is divided into the three following parts. The first proposes the definition and describes the resulting typology of Flight-to-Quality events. Taking a further step in this direction, the automated identification algorithm based on the total returns of the safe and risky asset classes is developed. This algorithm is then applied to the identification of the Flights-to-Quality out of Emerging Markets debt towards U.S. Treasury bonds. The considered time interval spans thirteen years from 1998 to 2010. As a result, a set of events to be used in further Flight-to-Quality analysis is obtained.

The second part of the second chapter is dedicated to setting up the model of Flight-to-Quality. The model investment universe comprises the two sub-universes, namely safe and risky asset classes. The dynamics of the investment flows between them becomes a base for the development of the Alarm Signal System envisaging the Flight-to-Quality identification on *ex-ante* basis.

The third part of the second chapter addresses the time behavior of safe and risky asset appetites metrics, this being the fundamental part of the Alarm Signal System. The mechanisms of the generation of alarm signals to warn of approaching Flights-to-Quality and their termination are explained. The proposed model of Flight-to-Quality is applied to study flights out of Emerging Markets debt investments to the quality of the U.S. Treasury bonds.

The third Chapter deals with the applications of the Alarm Signal System to the development of the diverse dynamic hedge strategies. The possible improvement in timeliness of financial polices represents an additional important field for the application of the Alarm Signal System based on the developed Flight-to-Quality model.

The Thesis closes with the conclusion, which summarizes the achievements obtained within the analyses of Flight-to-Quality phenomena and evaluates the applicability and efficiency of the proposed Alarm Signal System in terms of its usefulness to withstanding and reducing financial instability.

# 2. Literature Overview

The Flight-to-Quality phenomenon, characterized by mass investment migration from risky to safe assets, has attracted considerable attention from academic researchers and market practitioners in their attempts to comprehend the sources of financial instability and its outcomes. This literature survey addresses with the overview of the knowledge related to the riskiness of investment activities. The selected topics, which follow below, focus on the interpretations, measures, and manifestations of risk, which are important in the context of this research.

This Chapter is organized as follows. Firstly, the evolution of risk perception is presented through the development of the Portfolio Theory. Secondly, the survey of the literature dedicated to the analysis of the origins and consequences of financial crises and Flight-to-Quality phenomena along with the research targeting their predictability is performed. And thirdly, the revision of the diverse interest rate hedge strategies suitable to mitigate the undesirable risk related to the adverse changes in interest rates during financial turmoil and Flights-to-Quality is addressed.

## 2.1. Evolution of Risk Perception

As Flight-to-Quality is an event when investors run from assets perceived as risky to the investment instruments considered as a safe haven, for a purpose of the present work it is important to consider the proper concept of risk in full details. Hence, understanding this concept through the history of its development can provide valuable insights into the matter of risk.

The purpose of this part is to track the evolution of risk perception by economists and investors. The relevant to this issue literature is summarized in three sections. The first treats risk perception prior to and on the early stages of Portfolio Theory development. The second section covers the risk treatment via the standard deviation measure, being the foundation stone of the Modern Portfolio Theory, which is widely based on the mathematical and statistical tools. The third group of literature is dedicated to the risk concept within the Post-Modern Portfolio Theory, enhanced by the behavioral finance assumptions and downside risk measure proposition.

### 2.1.1. The Dawn of Asset Selection

The main feature of early investment theories is an assessing the risks and rewards of stand alone individual securities, rather than attempt to describe investment portfolio as a whole. Investors tried to capture the unique investment opportunity and related risk of each asset by the investigation of a company's history, current and future fundamentals, management, business model, etc. Investors identified those securities that offered the best opportunities for gain with the least risk, and then constructed a portfolio from them, using the so-called "*individual asset picking*" method. It was also the dawn of investments diversification: the correlation uses were not considered and only granularity was taken into account.

The literature related to risk investigation during the early stages of the Portfolio Theory could be classified into the three following groups: Profit Theories, Marginal Utility Theory, and its extension, Expected Utility Theory.

In fact, the former group represents the earliest investigation of risk, which was closely linked to the attempts of explaining the nature of profit.

#### 2.1.1.1. Profit Theories

Three Profit Theories can be distinguished in respect to the treatment given to the relationship between risk and profit. These theories are: Dynamic Theory, Risk Theory, and Knight's Theory. The concept of spreading the investment risk across many independent investments is not considered yet on this stage of the economic knowledge development.

The first attempt to find a link between profit and economic environment fluctuations is undertaken by Clark (1899). He proposes the Dynamic Theory of Profit. The author, classifying social circumstances into two states: static and dynamic, argues that profit is a result of dynamic changes in society. There is no risk for the entrepreneur in a static society, and therefore there would be no profit for the entrepreneur. Profits arise in a dynamic state due to the changes, which affect the demand and supply of commodities. Clark (1899) distinguishes such alterations as population and capital increase, improvement of the production methods, change in the form of industrial establishment, and multiplication of consumers` requirements.

The weakness of Clark's theory can be attributed to the absence of a link between the intrinsic risk, presented in a chosen business, and the dynamic changes in the society.

Additionally, the author omits to further investigate a difference between the foreseen and unanticipated changes.

Alternatively, Hawley (1907) develops the Risk Theory and makes an important contribution detecting that risk taking by the entrepreneur was the main condition of the future income increase. The author explains profit by considering it to be commensurate with risk. Since the entrepreneur undertakes the risk of business, he is entitled to receive profit as a reward. Hawley (1907) stated that "*the riskier the industry the higher its profit rate*".

Some of the shortcomings of Hawley's theory can be mentioned as follows:

- There is no functional relationship between risk and profit;
- Risk Theory disregards the businessman's ability to undertake risk;
- Risk is explained as a known term without deep analysis and definition of uncertainty.

Knight (1921), making further advances in risk investigations, formulates the concept of the two types of economic fluctuations: predictable, defining them as a measurable risk, and unpredictable, interpreting them as an uncertainty or immeasurable risk. Knight (1921) treats measurable risk as a situation where the entrepreneur can assign mathematical probabilities to the randomness, which he is faced with. In contrast, uncertainty or immeasurable risk refers to situations when this randomness cannot be expressed in terms of specific mathematical probabilities. Knight (1921) points out that profit is not due to all types of dynamic changes, as it is in the Clark's Dynamic Theory, but only due to changes that cannot be foreseen. The conception of unpredictable changes came to be called *Knightian Uncertainty* and is widely used by diverse authors to model Flight-to-Quality events, such as Caballero and Krishnamurthy (2008) among others.

Knight´s theory is followed by the development of the Marginal Utility Theory, and its extension the Expected Utility Theory. It is worth noting that, according to Markowitz (1992), these theories proposed initial mathematical approaches to risk quantification, which though remained purely theoretical being rather too complex to be applied in investment practice.

#### 2.1.1.2. Marginal Utility Theory

The next stage in the development of literature, related to the risk explanation during an early period of Portfolio Theory, is associated with the idea of the importance of marginal utility analysis of each individual assets added into the investment portfolio. Liquidity and diversification in terms of the spreading the investments across many independent risks are considered. In this way a theoretical base for a Modern Portfolio Theory is being prepared.

For example, Lavington (1921) describes the riskiness of assets with respect to their ability to be transformed into cash: the higher the speed of transformation the more protected the investor and the lower the rate of return. Further on, Robertson (1928) suggests that a chosen asset ought to be analyzed not only on its own but also from the point of view of its utility to increase the desired features of the existing investment portfolio, for instance, to improve profitability or increase liquidity.

Hicks (1935) analyzes the relationship between liquidity and risk through marginal analysis. He states that any particular investor may consider holding his assets in different forms depending on his exposure to the risk. The author classifies all spectrums of investment instruments based on their liquidity risk: cash, call loans, short-term loans, long-term loans, and material property, followed according to their decreasing liquidity. Hicks proposes that a decision on the investment in particular asset should be taken based on the analysis of relative prospects of return and relative risk factors.

He also distinguishes results of investing in one particular asset and in various separated securities and points out that the investors "*who have command of large quantities of capital, and are able to spread their risks, are not only able to reduce the risk on their own capital to a fairly low level – they are also able to offer very good security for the investment of an extra unit along with the rest*".

Chambers (1934) shares Hicks' idea of diversification putting it more popularly that "*the risk is less if the eggs are in a number of independent baskets*". Risks cancel each other if the wealth is spread across many independent risks.

#### 2.1.1.3. Expected Utility Theory

An extension of Marginal Utility Theory, Expected Utility Theory, provides rigorous approach of investor risk preferences and decision making under uncertainty. The "*risk and uncertainty*" debate distinguishes this group of literature into two parts.

The first is the expected utility theory with objective probabilities of von Neumann and Morgenstern (1944). Authors model the risk as a transformation of independent variables by a function that reflects the decision-maker's response to uncertain outcomes.

The second is the state-preference approach of Arrow (1953), Debreu (1959) and Pratt (1964) and is one of uncertainty. There are no assignments of probabilities.

It is also worth noting the intermediate theory by Savage (1954), based on expected utility with subjective probabilities or "*probability beliefs*", which can not be clearly attributed to one camp or another: on the one hand, the assignment of numerical probabilities, even though subjective, implies that it represents a choice under risk; on the other hand, these probabilities are merely expressions of what is ultimately amorphous belief and thus may seem more like uncertainty.

A precise and general solution for the economics of choices under uncertainty being a major advance in Expected Utility Theory, though not easily computationally feasible, is developed by Arrow (1965), who chooses a parallel course in respect to a good approximated solution, developed by Markowitz (1956). He proves the usefulness of quadratic approximation to the strategy of maximizing the expected utility of return that allows investor to choose portfolios based on mean and variance, which is widely spread under the name of the Modern Portfolio Theory. Levy and Markowitz (1979) compare the outcomes of various approximations to Expected Utility with the observed probability distributions, and which did the best was Markowitz Expected Utility proposed in Markowitz (1959). This expected utility is compatible with the normal distribution, which is a well-known base of the Modern Portfolio Theory.

### 2.1.2. Modern Portfolio Theory

The fundamental idea of Modern Portfolio Theory (*MPT*) is to measure risk and return of an investment portfolio as a whole instead of considering to analyze the diverse characteristics of individual selected assets as suggested by previous studies. *MPT* shows that all the information needed to choose the best portfolio for any given level of risk is based on three simple statistics: the mean return, the standard deviation of the returns, and the correlation with other assets' returns.

The body of *MPT* literature related to the analyses of risk can be divided into the three parts: the original Markowitz's approach (1952, 1959) with Tobin's (1958) and Sharpe's (1963) contributions, the initial Capital Asset Pricing Model (*CAPM*), and its extensions.

#### 2.1.2.1. Original Markowitz's approach

The revolution in the formulation of risk measure concept in the Investment Portfolio Theory is ascribed to the Markowitz (1952, 1959). He proposes quantitative framework of how investors can allocate assets into portfolio to optimally trade off risk versus return. Prior to the appearance of the Markowitz portfolio selection approach, the law of large numbers plays a crucial role in the investment risk reduction problem through diversification allowing in principal to turn variance of returns null by spreading risk across the assets providing identical returns. Markowitz has an important insight on this issue. He writes that "*the law of large numbers applies to a portfolio of securities, cannot be accepted. The returns from securities are too intercorrelated. Diversification cannot eliminate all variance*." Markowitz postulates that diversification benefits should be achieved through analyzing the correlation across securities. The risks of investments must be viewed in the context of the other risks to which investors are exposed.

Markowitz develops mean-variance assumption of the investment portfolio choice: expected return is measured by the mean of the probability distribution of portfolio returns, and risk by the standard deviation or variance of the distribution which provides a measure of the dispersion of possible returns around the mean value. A large standard deviation implies a high probability of wide deviations from expected returns, both positive and negative.

Markowitz proposes the techniques of linear programming to develop the *critical line* algorithm, which represents all feasible portfolios of common stocks that minimize risk for a given level of expected return and maximized expected return for a given level of risk. In a graphic form, in standard deviation versus expected return space, these portfolios fit the *efficient frontier line*, which represents the trade off between risk and expected return faced by an investor when he forms his portfolio.

Roy (1952) independently develops a similar mean-variance efficient set and proposes an objective function whereby individuals minimize the probability of a decrease in their wealth below the disaster level or, alternatively, minimum acceptable return. This approach is similar to the Markowitz model but the latter develops further and offers the investor the choice of the portfolio of assets that will give the required return at a minimum variance.

Tobin (1958) contributes to the Markowitz approach being the first who incorporates the risk-free assets into the mean-variance model of portfolio choice. He proves that investors would diversify their investments between a safe asset and a single portfolio of a large number of risky assets based on their degrees of risk aversion. This simplifies a set of efficient risk-return combinations, which could be represented as a straight line tangential to the *efficient frontier* and crossing the ordinate axis at the value equal to the return of a chosen safe asset.

Sharpe (1963) improves Markowitz portfolio optimization technique in terms of its practical implementation. He introduces a single-factor market model in which all the covariations of securities returns are explained by a single-factor. This dramatically reduces the computational burden of Markowitz's model by assuming that Tobin and Markowitz optimal portfolio of risky assets was in fact the market itself. Sharpe suggests analyzing various possible returns from a particular investment using two components: systematic (market) risk and non-systematic (individual) risk. Further, he assumes that specific risks are not correlated to each other due to their individual characteristics. The only correlation of assets, which can exist, is due to the influences of market conditions. Logically, Sharpe excludes systematic risk from the total risk, which makes it possible to avoid the computation of a huge number of covariances. According to Sharpe, it is necessary to calculate the market risk, which is the measure of market in the form of market indexes available nowadays on a daily basis, and the specific risk of investment. All the investor needs is to choose the market index (index funds), which fits his investment preferences and put it in, avoiding analysis of many individual stocks and bonds.

The discussed above foundations of the Portfolio Theory were aimed mostly on providing an actionable solution to a question about how an investor optimizing returns should address asset selection. A logical continuation of this issue is a study of economic equilibrium assuming that all investors optimize their portfolios in a manner described by the Portfolio Theory rule based on efficient frontier. This topic is addressed in a number of works dedicated to the Capital Asset Pricing Model (*CAPM*).

#### 2.1.2.2. Capital Asset Pricing Model

The next stage in the development of investment risk perception in the *MPT* period is related to the *CAPM*, which builds on the Markowitz's model and refines the notions of systematic and non-systematic risk. The *CAPM* turns the Markowitz's algebraic mean-variance approach into a testable prediction about the relation between risk and expected return by identifying a portfolio that must be efficient if asset prices are to clear the market of all assets. *CAPM* provides the first consistent framework for answering the question of how the risk of an investment should affect its expected return. The *CAPM* is developed by Sharpe (1964), Lintner (1965), and Mossin (1966).

In the *CAPM*, the risk associated with an asset is measured in relationship to the risk of the market as a whole. Consequently, *CAPM* introduces the concept of *Beta* to assess the market risk. This measure can be understood as a marginal contribution of the certain security to the risk of a well-diversified portfolio. In other words, it offers a method of measuring the risk of an asset that cannot be diversified away.

If *Beta* is greater than one, it means that by adding this security, investor augments the risk of the portfolio and its return. If *Beta* is less than one, it means that investor is dealing with the decreasing overall risk of the portfolio and its return. Consequently, assets with higher *Betas* are more sensitive to the market. If the investor knows the *Beta* of a certain security he will also know what the value of expected return will be.

#### 2.1.2.3. Extensions of the CAPM

The third part of *MPT* literature related to the risk assessment is associated with the various extensions of the original *CAPM*. Generally they could be systemized into the three main groups: Arbitrage Pricing Theory (*APT*), Consumption Capital Asset Pricing Model (*CCAPM*), and Multi-Factor Models.

Ross (1976) proposes to use multiple *Betas* in his *APT* model. In alternative to the *CAPM*, which has only one overall market risk factor, the *APT* has multiple unidentified risk factors. The examples of unidentified risk factors can be macroeconomic variables such as interest rate, inflation rate and so on. Each risk factor has a corresponding *Beta*.

Breeden (1979) and Lucas (1978) introduce the *CCAPM* concentrated on investor's consumption preferences. They measure the risk of a security by the covariance of its return with per capita consumption. Instead using *Beta*, to calculate the market risk, authors propose to measure how much the entire stock market changes relative to the consumption growth. The logic is that risky assets create uncertainty in consumption because investor's spending becomes uncertain due to the uncertainty of his income, which reflects a decision to invest in risky assets.

The one of the examples of Multi-Factor Model is Fama and French's (1993) approach. They test diverse results of the *CAPM*, and show that, on average, a Portfolio's *Beta* explains about 70% of its actual returns. Consequently authors propose the Three Factor Model consisted of three risk factors. The most important continued to be a *Beta* factor from the *CAPM*. The second factor is size, which compares the weighted average market value of the stocks in a portfolio to the weighted average market value of stocks on the market. Authors show that the small stocks are more risky and generate higher returns than large stocks. The third factor is a book-to-market ratio of equity. Fama and French (1993) show that a combination of *Beta*, size, and book-to-market value explain 95% of a diversified portfolio's return.

Other examples of Multi-Factor Models are the following. For instance, it is worth noting the Two-Factor Model proposed by Black (1972). He eliminates the assumption of safe asset and the investors' possibility to borrow and lend at the risk-free rate. Another Two-Factor Model is developed by Brennan (1993). He proposes to measure, along with the market *Beta*, an active management risk, which is defined as the normalized (to the benchmark's variance) covariance between the asset excess return and the excess return of the market over the benchmark index.

Summarizing the results of various extensions of the original *CAPM*, according to Bruner et al. (1998), Graham and Harvey (2001), and Dhankar and Singh (2005), Brealey et al. (2007), among others, the *CAPM* is found to be the most favored model of practitioners and academics in order to rigorously enough address conceptual and quantitative issues related to risk. It still remains a cornerstone of financial economics although other theories were created since then including, in a first place, the so-called Post-Modern Portfolio Theory.

### 2.1.3. Post-Modern Portfolio Theory

The third stage in the development of knowledge related to the risk perception can be ascribed to the further evolution of *MPT*, which results in the Post-Modern Portfolio Theory (*PMPT*). The *PMPT* literature, which contributes into the formulation of risk notion, can be divided into two main parts. The first deals with the evolution of downside risk measures. The second is related to the incorporation of behavioral finance concepts into the risk treatment.

#### 2.1.3.1. Downside Risk Concept

Downside risk measures a security's potential to suffer a decline in price if the market conditions turn bad. It can be thought of as an amount that can lose on a stock, bond or other security in adverse situations. The research of downside risk measure can be classified into the three evolutionary groups. The first part is originated from the *MPT* period and its theoretical definition of downside risk measure is required for the program algorithms, which are created in the period of *PMPT* development. The second group of works is related to the proposition of the Lower Partial Moments (*LPM*) framework to assess downside risk. The third part focuses on the recent computational algorithms used for the downside risk calculations.

The idea of the importance of downside risk measure appears still in the early period of the *MPT* foundation. The essential in the development of downside risk measure is the observation made by Roy (1952) that investors care differently about downside losses than they care about upside gains. Investors prefer safety of principal first, when dealing with risk.

Markowitz (1959) develops this thought further. He makes two observations. The first is that only downside risk or safety first is relevant to an investor, and the second is that security distributions may not be normally distributed. Standard deviation and normal distribution do not satisfy the concept of risk actually applied to investment decisions. Markowitz provides two suggestions for measuring downside risk: a semi-variance, computed from the mean return or below mean semi-variance, and a semi-variance, calculated from the target return or below target semi-variance. The two measures compute a variance using only the returns below a mean return or below a chosen target return. Markowitz calls these measures partial or semi-variances. As it is noted by Sharpe (1964), due to the computational limits at the time of research, Markowitz (1959) stays with the mean-variance risk measure to proceed with his portfolio selection analysis.

The theoretical research, supporting the usefulness of Markowitz's measure of downside risk by semi-variance instead of variance, is performed by Quirk and Saposnik (1962), and Mao (1970) among others.

The computer algorithm program to calculate semi-variance, as well as mean variance, is created by research team under the supervision of Philippatos (1971) with the contributions of Porter et al (1973), Porter (1974), and Porter and Bey (1974).

The next progress in the downside risk measure evolution can be ascribed to the moving from semi-variance measure to the *LPM* approach proposed by Bawa (1975) and Fishburn (1977). This measure of downside risk is more general than semi-variance. Semi-variance is computed as the average of the squared deviations below the mean return while for example the second *LPM* is usually computed as the average of the squared deviations below a target return. The *LPM* risk measure can be based on many Neumann-Morgenstern utility functions instead of one quadratic utility function in case of variance or semi-variance risk measures. This makes possible to incorporate the more aspects (if not even the whole spectrum) of human behavior into the investment portfolio risk models such as risk seeking, risk neutrality, risk aversion, and to describe it mathematically.

The *LPM* algorithm programs are provided by Harlow (1991) and Nawrocki (1991, 1992) among others.

The third group of literature, related to the downside risk assessment, includes studies developing the applications of downside risk concept in practice.

According to Sortino (2001) the first interest in downside risk in an applied sense appears with the extensive tests performed by Sortino and Meer (1991) demonstrating the downside deviation (below-target semi-deviation) as a tool for capturing the essence of downside risk. Sortino and Price (1994) and Rom and Ferguson (1994) contribute in areas of the performance measurement. Rom and Ferguson (1997/1998) summarizes the use of downside risk measures for performance measurement.

#### 2.1.3.2. Influence of Behavioral Finance

The second contribution of the *PMPT* into the development of risk concept is the incorporation of behavioral finance features into the investment science. Behavioral finance is a part of financial economics, studying the models in which some agents' behavior can be not completely rational. Following Fama and French (1993, 1996) among others, the traditional *MPT* assumptions of expected utility maximization with rational investors in the efficient markets cannot be confirmed by the available investment data. Consequently behavioral finance has emerged in the response to the difficulties faced by the traditional paradigm based on economic agents' rationality.

According to Barberis and Thaler (2003) behavioral finance literature is based on the two approaches: *limits to arbitrage* and psychology.

### ***Limits to arbitrage***

*Limits to arbitrage*'s works study diverse models where rational and irrational traders interact, and show that if irrational traders cause deviations from fundamental value, rational traders will often be powerless to do anything about it. Detailed theoretical analysis of this issue can be found in De Long et al. (1990), and Shleifer and Vishny (1997), and evidence of *limits to arbitrage* is observed by Harris and Gurel (1986), Shleifer (1986), Froot and Dabora (1999), Wurgler and Zhuravskaya (2002), and Lamont and Thaler (2003) among others.

### ***Psychological Theories***

According to Barberis and Thaler (2003), in order to investigate the structure of deviations from fundamental value, the second approach of behavioral finance dedicated to the human psychology arises. Following Balzer (2001), the psychological perception of risk plays an important role in the formulization of the risk concept in *PMPT*. Psycological theories generally can be divided into two parts. The first deals with the specification of how agents form their expectations. The second treats the prospect theory, which is descriptive theory of choice under uncertainty in contrast to expected utility theory, which is normative rather than descriptive.

The main patterns regarding how people form their beliefs and expectations under uncertainty can be found in Shleifer (2000), Hirshleifer (2001), Fromlet (2001), and Barberis and Thaler (2003), Shiller and Akerlof (2009) many among others.

Overconfidence is described by Fischhoff et al. (1977), Alpert and Raiffa (1982), Barber and Odean (2001), Ritter (2003) among others. The latter explains little diversification by the investor's overconfidence.

Tversky and Kahneman (1974) identified the influence of human heuristics on the decision-making process. People often use heuristics to reduce complex problem solving to more simple judgmental operations. Following Tversky and Kahneman (1974), three of the most popular heuristics include representativeness, anchoring, and availability biases.

Addressing the representativeness heuristic Ritter (2003) writes that equity returns in the U.S. and Western Europe during the 1982-2000 have been high and many people begin to believe that high equity returns are "*normal*". Amir and Ganzach (1998) explain errors of earning forecasts by the fact that heuristic individuals anchor on prior outcomes. Shiller (2005) describes quantitative and moral anchors influenced the financial market.

In parallel, the prospect theory is undergoing development as a tool to better understand the investment decision-making. Kahneman and Tversky (1979) present a critique of expected utility theory and develop an alternative model, which they call Prospect theory. Prospect theory focuses on changes in wealth, whereas expected utility theory, and consequently *MPT*, focuses on the level of wealth. Kahneman and Tversky (1979) find empirically that people underweight outcomes that are perceived more certain in comparison with outcomes that are obtained with certainty.

Groot (1998) studies one hundred wealthy investors to determine if they make decisions in a manner consistent with expected utility theory or behavioral finance theory. He finds that approximately half the questions have been answered in a manner consistent with utility theory and the other questions have been answered in a manner consistent with behavioral finance. But most of these investors say they want "*wealth growth that is as stable as possible where a trade-off between risk and return has been made*".

According to Shefrin (2002) investors seek upside potential with downside protection. Olsen (1998) writes, "*Investors desire consistency of return and therefore choose decision processes that preserve appropriate future financial flexibility*". Rather than maximize the expected return, investors want to maximize a “satisfying” strategy allowing them to avoid downside risk manifestations.

## 2.2. Downside Risk: Financial Crises and Flights-to-Quality

A situation when downside risk or a performance below the minimum acceptable return is manifested by strong, multiple and widely spread across the financial industry shortfalls can be considered as a financial crisis. One could think of a crisis as a Flight-to-Quality event, when investors rebalance their portfolio flying from risky to safe assets, as of an extraordinary strong Flight-to-Quality which not merely results in a limited duration shock reshaping investment activity, but transforms the initial tendency of growing imbalance between risky and non-risky assets into a vicious circle. Due to the interrelationship between the concepts of crisis and Flight-to-Quality phenomena, it is important for this particular research to survey the literature related to the origins, consequences, and forecasting methodologies of both, crisis and Flight-to-Quality.

This part is organized as follows. Firstly, the main theories of financial crises proposing different views on the nature of these events and their empirically observed consequences are presented. Secondly, the literature, which addresses diverse forecasting techniques either based on the fundamentals of economy or on alternative multidisciplinary approaches described in recent studies are surveyed. The third section focuses on advances in a knowledge regarding the Flight-to-Quality phenomena.

### 2.2.1. Financial Crises: Theoretical and Empirical Studies

Financial crisis is a phenomenon, which accompanies since almost unmemorable times the economic track of humanity. Varied research of this event has become extremely popular once again in a recent past following the Global Financial Crisis started in the summer of 2007. The strength of this event overcame the expectations of the major part of fundamental and applied researchers and thus can be considered as a great surprise to the financial community in general.

As an introduction to this section it would be useful, to give general definitions of varied types of crises discussed bellow, assuming, however, the fact that there are no universally agreed interpretations of these events, and that crises almost always can be interrelated between each other and a crisis of one type may cause the other.

*Economic crisis* can be defined as a long-term economic state characterized by unemployment and low prices and low levels of trade and investment.

Common view on *financial crisis* is that it is the situations of strong disruptions in financial markets when financial institutions and assets suddenly lose the most part of their value. Following Fourcans and Franck (2004), there are three broad categories of financial crises: debt crises, banking crises and currency crises. *Debt crises* take place when a government fails to meet payments on its external or domestic debt obligations or both. *Banking crises* occur when actual or potential bank runs or bankruptcy force banking institution to suspend the convertibility of their liabilities. According to Krugman (2000), *currency crises* can be characterized by the following key element. This is when the most part of investors fleeing a currency out due to the fear that currency might be devalued, in turn fueling the very devaluation they anticipated.

Also it is worth to define the concept of *business cycle* as it is used in the discussion of the Crises Theories below. This term usually means the period of time during which an economy moves from a state of expansion to a state of contraction, before expanding again.

This section focuses on the literature overview of theoretical and empirical knowledge related to the investigation of the crisis nature, its moving economical forces and conditions for it to happen.

#### 2.2.1.1. Theoretical Models of Financial Crises

According to Allen and Gale (2007), the theoretical models of crises, explaining its nature, can be generally systemized into the following six groups: Financial Panic, Business Cycle, Inconsistent Government Macroeconomic Policies, Government Guarantee Models, Amplification Theories, and Bubble Collapse. These sub-sets are interrelated with each other and are neither mutually exclusive, nor completely exhaustive, but offer a meaningful approach to the structuring the survey of financial crisis origins.

It is worth noting that Financial Panic and Business Cycle theories are mostly related to the analysis of the banking and currency crises.

***Financial Panic models***

The early Financial Panic models are developed by Kindleberger (1978), Bryant (1980) and Diamond and Dybvig (1983). These models and their extensions view financial panic episodes as crises that henceforth are treated as random events unrelated to changes in a real economy.

Kindleberger (1978), investigating the long history of financial crisis, finds that crisis occur spontaneously as a result of "*mass hysteria*" or panic. He distinguishes three phases of the asset pricing process: mania, panic and crash. Manias take place in the markets following the unexpected good news and consequently this changes the risk perceptions and causes investors to be overoptimistic and irrational. Panics occur after the mania has died out, and investors begin to speculate in the opposite direction. Panics are defined as the movement away from illiquid assets to money or cash. Crash is the final phase of this process entering the stage after the panic with everyone expecting a crisis and acting as if it is about to occur.

Bryant (1980) and Diamond and Dybvig (1983) propose Financial Panic models, which are based on the existence of multiple equilibriums or "*sunspots*", one of which is a panic, and consider consumers with random demand for liquidity. These are the classic benchmark models for a bank run.

Bryant (1980), developing further on the Samuelson's (1958) pure consumption-loans model, shows that bank runs happen due to the situations when risky bank's assets subject to random conjuncture do not anymore cover a nominal amount of existing liabilities, so depositors become nervous and decide to quickly cut their losses.

In Diamond and Dybvig`s (1983) model, banking crises are provoked by different type of expectations including the apparently irrational people behavior. This behavioral pattern results out of a shock that determines whether each individual wants to consume now rather than later. However, even those wanting to consume later may want to withdraw their money if they think a bank run will occur, and if they do, the bank run exhausts the bank's liquid assets. Depending on whether depositors coordinate on the run or no-run equilibrium, a crisis does or does not occur.

Carlson (2002), based on the analysis of individual behavior, draws two models of financial panic: the "*random withdrawal theory*" and the "*asymmetric information theory*". The former states that people run to banks thinking the bank's liquidity insufficient to satisfy all customers' needs. The latter stresses on poor information available: since people are unaware of the institutions in trouble, they withdraw from all banks of the area.

Many other authors contribute into the analysis of the crisis' origins through the development of the Financial Panic models. Among them, for example, Sachs (1984), Wallace (1988, 1990), Champ et al. (1996), Green and Lin (2000), Morris and Shin (2001), Goldstein and Pauzner (2005), Andolfatto and Nosal (2006), Ennis and Keister (2006), He and Xiong (2009), and Cavalcanti (2010).

These models, if considered as stand alone, form a certain isolated domain of knowledge, but bearing in mind that panic can be seen as an integral phase of business cycle, the Financial Panic models are closely related to the Business Cycle models, which are discussed below.

***Business Cycle models***

The main idea of the Business Cycle theory is that crisis is an essential part of business cycle and originates out of shocks shaking financial fundamentals. This statement represents the main difference between Business Cycle models and Financial Panic models. The latter class treats crisis as one of possible multiple equilibriums of the system implying that crisis is not essential to the economic activity, contrary to the very basic assumptions of the Business Cycle theory-based models where panics are not random events.

In accordance to Mitchell (1941) economic downturn reduces the value of bank assets, raising the possibility that banks are unable to meet their commitments. If depositors receive information about an impending downturn in the cycle, they will anticipate financial difficulties in the banking sector and try to withdraw their funds. This attempt will precipitate the crisis.

As valuable contributions to Business Cycle theory can be cited the works by Black (1987, 1995) who proposes that the general risk-return trade-off exercises its influence on a business cycle and consequently results in significant sectoral shifts of investment activities.

Considering this issue more deeply for a banking sector, Jacklin and Bhattacharya (1988) propose a model according to which bank runs are not random since they appear as a response to changes in expectations about the results of bank investments. During the first period, a certain proportion of depositors obtain an information signal indicating a new probability of the failure of the projects in which a bank has invested. The authors are able to obtain the so called minimal reported probability of failure, such that for higher probabilities, should they become somehow revealed, the worrying depositors prefer to withdraw their money the earliest possible. They also find that this minimal reported probability depends negatively on the variation of random investment results.

Allen and Gale (1998), incorporating risk through random asset returns, develop a model which is consistent with the business cycle view of the nature of banking crises as coming out of an intrinsic cyclicality of economic conditions. They assume that everyone, including depositors, can observe a leading economic indicator that is perfectly correlated with future asset returns. Banks invest in two kinds of assets: a risky, illiquid asset (the long asset) and a safe, liquid asset (the short asset). Based on these simple assumptions, the authors' model is used to investigate the costs and the benefits of banking crises. They also show that in order to reduce a negative impact on the society, the central bank intervention of the right kind can lead to a Pareto improvement in welfare.

Business Cycle models of banking crises are also developed by Chari and Jagannathan (1988), Hellwig (1994), Alonso (1996), Samartin (2003) among others.

Allen and Gale (2004) defend the idea that the existence of financial crashes is essential to unleash latent efficiency, which sometimes can be restricted by Pareto-efficiency of Walrasian equilibrium conditions. Authors present some circumstances when financial crises have no negative influence on the welfare and demonstrate that the assumption of optimality of avoiding crises cannot always be taken as axiomatic.

Recent examples of Business Cycle models include Fostel and Geanakoplos (2008) and Von Goetz (2009) among others. According to these models, agents behave rationally and respond to evolving news. Responses to the news become especially pronounced in environments of asymmetric information, and can deliver large changes in leverage and asset pricing. These models are capable to explain why some credit crashes are much more severe than others: the severity is explained via strength of exogenous shocks acting on the financial conditions of the system (leverage, liquidity, etc.) in times when important news arrives.

***Inconsistent Government Macroeconomic Policies***

The third type of crises models is related to the government financial and exchange rate policies that are inconsistent with stability.

Krugman (1979) develops so-called "*first-generation*" canonical crises model designed to explain the problems experienced by a number of Latin American countries in the 1970 and early 1980. These problems arise from imbalances in the public sector (balance of payments) caused by speculation and decline in international reserves. Krugman (1979), based on the Kouri's (1976) model, shows how a fixed exchange rate plus a government budget deficit leads to a currency crisis. Government may be running a deficit that is financed partially by expanding the money supply. The resulting inflation acts as a tax. This can be inconsistent with a fixed or controlled pegged exchange rate and, hence, trigger a currency crisis. Flood and Garber (1984), Connolly and Taylor (1984), Sachs (1986), Wijnbergen (1988), Dooley (2000) extend the work of Krugman (1979).

"*Second-generation*" models, being popular among mid 1980 and 1990, improve its predecessor considering government policy to be less mechanical than in the "*first-generation*" models: government chooses whether or not to defend a pegged exchange rate by making a trade-off between short-run macroeconomic flexibility and longer-term credibility. For example, Obstfeld (1986, 1994, 1996), author of the basic model of the "*second-generation*", focuses on expectations of domestic agents in respect to a decrease of the exchange rate and considers a devaluation as a government's decision. The result is that the financial crisis may appear even if the fundamental variables are favorable and there are no speculative assaults. Author shows how a conditional government policy can lead to multiple equilibria – one without a speculative attack and one with a speculative attack. The existence of multiple equilibria and uncertainty about the timing of an attack permit a discontinuous jump in the exchange rate. The outcome of the attack depends on the resources the government is willing to commit to maintain the exchange rate. Contributions into the Obstfeld's (1986) model can be found in Calvo (1988), Mishkin (1992) among others.

"*Third-generation*" models appear after the financial crisis of East Asia in 1997 – 1998. These models investigate diverse relationships between a monetary crisis, on one hand, and the fragility of the financial sector, contagion from other countries, and role of microeconomic distortions, etc., on the other. In respect to the "*third-generation*" models, which address the inconsistency of the macroeconomic policies, could be mentioned an approach developed by Allen and Gale (2004). In accordance with their model, there is a certain negative impact of a government intervention in preventing financial crises. In this case, the Adam Smith's invisible hand works in a sense that a central planner with the same information could not Pareto-improve on the market's allocation. In this idealized world, there is no possibility of market failure and, hence, no possibility of welfare-improving government intervention.

But in reality things seem to be different. For instance, it is worth noting that since the very beginning of the recent Global Financial crises, the theoretical models, supporting the usefulness and necessity of governmental regulation, become widely popular; see for example, Caballero and Krishnamurthy (2008), Mishkin (2009), Giannone et al. (2010), Gameiro and Sousa (2010), Brock and Manski (2011) among others.

***Government Guarantee Models***

The key goal of the Government Guarantee models is to investigate how regulator should behave in order to prevent or overcome crises. These models focus on appropriate rules, but also consider inadequate government regulation and bailout rules as the cause of crisis.

Gorton and Huang (2004) study why governments bailout banking systems in distress and conclude that a bailout policy could be considered as a guarantee of an additional liquidity source at downturn conditions and, hence, guarantees a better stability and improves welfare.

Morrison and White (2005) analyze a general equilibrium model in which the regulator can learn the success probability of banks' projects, and impose capital adequacy requirements. This way, a regulator with a strong reputation can alleviate moral hazard. They show that the appropriate policy response may be to tighten capital requirements to improve the quality of surviving banks.

On the other hand, Repullo and Suarez (2008, 2010) are concerned with the procyclicality of banking regulations. Banks hold capital buffers to smooth their capacity to lend over the business cycle. They show that the Basel II agreement changes the behavior of these buffers from countercyclical to procyclical. Additionally, they find that the higher buffers maintained in expansions are insufficient to prevent a significant contraction in the supply of credit at the arrival of a recession. Generalizing, inadequate government attempts to guarantee financial stability could lead to the crises themselves.

***Amplification Theories (Contagion and Financial Fragility)***

Contagion and Financial Fragility become important concepts in the crisis models after the appearance of the "*third-generation*" inconsistent policy models and continue to be widely used in the analysis of the crises nature. Financial Fragility can be characterized as a phenomenon when a small shock has a large effect on the financial system. One of the mechanisms for this may be that the financial shock spreads geographically and exactly in this sense it is similar and closely related to illness contagion processes.

Although numerous theories of contagion exist in literature, they could be generally systemized into two closely interrelated groups. The one addresses fundamental causes of contagion, which include common shocks, trade and financial linkages, and the other focuses on the investors' behavior as an origin of crises expansion.

Investigating fundamental causes of contagion, Calvo et al. (1996) and Masson (1999) model such common or global shocks as changes in interest rates, currency exchange rates, and commodity prices.

Foreign trade interdependencies are also widely used in crises models as a fundamental cause of contagion. A crisis in one country can cause a reduction in income and corresponding reduction in demand for imports, thereby affecting exports, the trade balance, and related economic fundamentals in other economies through direct trades and commercial exchange. Theoretical literature related to the trade linkage can be found in Glick and Rose (1999), Corsetti et al. (2000), and Forbes (2002) among others.

Another major group of fundamental causes of contagion represents financial linkages through the bank lending or portfolio investment. For example, Allen and Gale (2000a) demonstrate that in times of excess of liquidity (when the liquidity demand is inferior to the liquidity supply), the interconnected banks and incomplete interbank market are factors, which can cause contagion effects. Van Rijckeghem and Weder (2001), Vance and Dungey (2007), and Caballero and Krishnamurthy (2009), among others contribute to the development of theoretical models using financial linkages assumption as a cause of crises spreading.

In addition to fundamental causes, the other major group of theories explaining contagion is based on investors' behavior including liquidity problems, incentive problems, informational asymmetries, market coordination problems, and investor reassessment. It is worth noting that there is some overlap between theories classified as fundamental causes and investors' behavior.

Diamond and Rajan (2001), analyzing the role of the bank in the solvency of illiquidity problem, characterize bank as a financial intermediary with a weak capital structure using its collection skills on behalf of investors by issuing demand deposits. Authors conclude that bank plays an important role in the liquidity creating. It becomes possible due to its capital structure fragility. Existence of stabilization policies, aimed at the strong capital requirements, leads to reduction in the liquidity creation.

Studying further liquidity problem and crash event, Diamond and Rajan (2005) conclude that bank crashes are contagious and are characterized by economy-wide negative effects. These effects are caused by bank`s influence on real production decisions of their clients – entrepreneurs. It is not important whether there exist links between banks or not, as it is in Allen and Gale (2000a) model, contagion has place anyway when liquidity demand exceeds liquidity supply. Other models, explaining contagion via investors' behavior, could be found in Chang and Majnoni (2001), Freixas and Holthausen (2005), Broner et al. (2006). As an example of the recent research on this issue, related to the current Global Financial Crises can be cited the Brunnermeier's (2009) approach. The author investigates several amplification mechanisms such as fire-sale externalities and network effects bringing about counterparty credit risk and gridlock risk. These mechanisms are used to enlighten the state of pre-crisis finance. Author points out that each standalone financial institution has an individual incentive to take on too much leverage and to have excessive mismatch in asset-liability maturities. While interconnected with other financial institutions the each one´s riskiness and the overall riskiness of the system is considerably amplified due to the contagion spreading via opaqueness of interconnected obligations.

***Bubble Collapse***

Financial crises often follow the so-called "*bubble*" explosions resulting in collapses of the respective asset prices. The Global Crisis that started in 2007 provides a perfect example as follows the U.S. subprime mortgage bubble bursting.

There are a number of theories that can explain how bubbles can arise. For instance, Allen and Gale (2000b) develop a model of boom and bust that relies on the existence of an agency problem. Authors observe that the growth in asset prices usually precede, with a certain interval, the beginning of financial crises. This is caused by three factors. The first cause is related to the intermediate relationships in the banking sector: financial liberalization or credit expansion accompanied by an increase in the prices for assets. The second phase is bubble burst and asset prices collapse. The third step is a bankruptcy of many economical agents that have borrowed to buy assets at inflated prices. Chang and Velasco (2001) develop their own model, which for emerging markets crises leads to the same conclusions as the previously cited work of the Allen and Gale (2000b). Chang and Velasco (2001) demonstrate that financial liberalization of domestic banking system, increasing foreign capital inflows, can result in banks` illiquidity, and, ultimately, could provoke financial crises.

Other theoretical research addressing bubble modeling can be seen, for example, in Tirole (1982, 1985), Allen and Gorton (1993), Allen et al. (1993), Abreu and Brunnermeier (2003), Scheinkman and Xiong (2003), Brunnermeier and Nagel (2004), and Hong et al. (2008).

Additionally, as a recent example of bubble bursting models can be cited approach developed by Makarov and Plantin (2012). Authors analyze changes in house prices in an economy where banks grant mortgages to liquidity-constrained households to finance a fixed supply of homes. Households' aggregate debt capacity drives the aggregate demand for homes. Home supply at a given date stems from foreclosures in case of default, sales motivated by the acquisition of a larger home, and sales that follow exogenous moving decisions. Market-clearing home prices in turn drive aggregate debt capacity. The model generates interesting insights into the impact of lower refinancing costs on housing bubbles and equilibrium conditions.

#### 2.2.1.2. Empirical Studies of Financial Crises

***Financial Panic and Business Cycle***

The large body of empirical literature related to the analyses of crisis seeks an answer on what approach is the more appropriate for the crisis's nature description: Financial Panic or Business Cycle models. Some empirical studies presenting the evidence that these both models are relevant and important for comprehension of the sources of crises are mentioned below.

For example, Friedman and Schwartz (1963), analyzing the crises, happened in the United States within the 1867-1960 years, advocate the view that many bank crises are resulted from panics. Authors prove this statement based on the unexpectedness of banking distress during the panics that they identify, and the absence of collapses in relevant macroeconomic time series prior to those banking crises. Friedman and Schwartz find that the time series of aggregate personal income, aggregate industrial production, wholesale prices, long-term government bond yields, and aggregate stock prices do not move adversely prior to banking crises in ways that seem capable of explaining their decrease and the collapses of bank deposits that occur during the banking crises.

Gorton (1988) conducts an empirical study to differentiate between the panic view and the business cycle view of banking crises. He finds evidence consistent with the view that banking panics can be predicted by the business cycle. Author shows that banking crises are triggered by the business cycle rather than some extraneous random variable.

Calomiris and Gorton (1991) conclude that the empirical evidence of crisis do not support the panic view. Panics happen near business cycle peaks. They find that stock prices fall the most during the pre-panic periods, suggesting that the crises are caused by fundamental factors.

Calomiris and Mason (2003) perform econometric study of the causes of the four bank distresses during the Depression, namely in late 1930, mid 1931, late 1931, and early 1933. They find that the first three crises are in accordance with the Business Cycle model assumptions and the fourth is panic-based.

Modern banking systems have increased in complexity over the last two decades creating various innovations related to the financial instruments to transfer credit risk. However, banks remain equally sensitive to panics and runs as they were at the beginning of the previous century. As Gorton (2009) finds the evidence, that in the summer of 2007 holders of short-term liabilities refused to fund banks, expecting losses on subprime and subprime-related securities. As in the classic panics of the 19$^{th}$ and early 20$^{th}$ century, there were runs on banks.

Gorton and He (2008), empirically testing the relative bank outcomes, derive that credit crunches happen periodically on a certain phase of the business cycle, the phase which is characterized by the considerable spreading of negative information regarding the bank performances and by the presence of the contagion’s features.

***Amplification Theories (Contagion and Financial Fragility)***

There is a considerable body of empirical literature dedicated to the contagion, which leads to the crises. Some of these empirical research focuses on examining asset prices and market co-movements during the period of crises. As an example of these studies could be mentioned Walti (2003), Bekaert et al. (2005), and Corsetti et al. (2005) among others. They find that correlations increase in equity markets during hectic periods, pointing to the presence of contagion. However, according to Hartmann et al. (2004), equity markets are twice as likely as bond markets to crash simultaneously.

On the other hand, Forbes and Rigobon (2002), based on empirical asset correlation analysis, refuse the existence of contagion at all. Authors point to the presence of high level of market co-movement in all periods, not only in time of crises. This evidence they refer to as interdependence. Flavin and Panopoulou (2009) demonstrated the similar with Forbes and Rigobon (2002) results.

The importance of trade and financial channels of contagion is also widely used in empirical studies to test the contagion models. For example, Forbes (2004) utilizes firm-level data to examine the exact channels through which crises spread.

Castiglionesi and Navarro (2007) show that there is a positive probability of bankruptcy and propagation of a crisis across regions when banks keep interbank deposits and may engage in excessive risk taking if they are not enough capitalized.

Financial distress in the banking system appears to be a concern for the economy as a whole. For instance, Dell'Ariccia et al. (2008) provide evidence that bank distress contributes to a decline in credit and to low *GDP* growth by showing that sectors more dependent on external finance perform relatively worse during banking crises.

In accordance with Allen et al. (2009), the developments after Lehman Brothers' crash in September 2008 suggest that contagion is indeed a serious problem. However, contagion did not manifest itself as a wave of failures suggesting a more complex phenomenon that is currently not well understood. Thus a more complete understanding of contagion is desirable before adequate policy responses can be thoroughly designed.

***Government Policies***

The considerable body of empirical literature, related to the crises analysis, deals with the verification of appropriateness of the government policies. Some of the recent studies on this issue are presented below.

For example, Sterling (2009) tests the *Bloomberg Financial Conditions Index* developed in response to the financial crises in 2008 by Rosenberg (2008, 2009). Sterling shows that this indicator can help to calibrate the degree of effectiveness of policy measures in restoring growth in the aftermath of a significant financial shock. Based on the *Bloomberg Financial Conditions Index*, author argues that the government decision not to rescue Lehman Brothers is an error, which represents an immediate and massive shock to the financial system and trigger for the fall 2008 panic. On the other hand Taylor (2009), in contrast to Sterling (2009), provides empirical evidence that government actions and interventions caused, prolonged, and worsened the financial crisis. Particularly, his empirical studies support government policy decision not to bailout the Lehman Brothers in order to prevent its bankruptcy in September 2008.

Walti and Weder (2009) focus on the analyses of bond market crises in emerging economies. They empirically find a set of interactions between favorable external conditions, sound macroeconomic policies and the presence of an IMF program, which contribute to shorter bond market crises.

### 2.2.2. Conventional and Alternative Techniques to Forecast Crashes

Financial world as well as a whole world are full of challenges and follow their own rules. Humanity, by its nature, tries to comprehend these laws and to design forecasting mechanisms to prevent disasters and other undesired events in order to avoid their negative impacts. This section surveys the literature addressing the possibility or impossibility to forecast crisis events. It is divided into two main subsections. The first deal with the conventional techniques to forecast financial downturns and the second subsection is focused on alternative approaches to predict crises. Additionally, some references, which describe pessimistic view on the possibility to predict crises, are presented.

#### 2.2.2.1. Conventional Techniques to Predict Financial Crises

In order to systemize all the existing variety of conventional techniques traditionally used for crises forecasting, they are divided into two interconnected modes: based on microeconomics and macroeconomics concepts. Micro mode techniques are used to predict bankruptcies on microeconomic level, such as, for example, defaults, potentially multiple defaults of individual banks and corporations. Consequently, macro mode methods are employed to analyze aggregate data and to forecast crises and major financial disasters on the macro level of economy, such as, for example, asset bubbles formations and their consecutive bursts (fairly exemplified by the recent subprime crisis on the mortgage market), credit crunches (runs on banks, drastic increases in the cost of funding), drop in liquidity of assets, all being different manifestation of financial crises.

*Microeconomic forecasting techniques*

The micro mode forecasting techniques aim to develop models for forecasting defaults of stand alone individual banks or corporate entities. The inputs of these models usually are similar to bank supervisory rating systems based on the financial ratios of banks. The widely known rating system is the U.S. one named *CAMELS*, which is an abbreviation and stands for *C*apital Adequacy, *A*sset Quality, *M*anagement, *E*arnings, *L*iquidity, and *S*ystemic Risk indicators used as input data.

In accordance with the comprehensive survey on techniques, used to predict bankruptcy in banks and firms, performed by Kumar and Ravi (2007), all forecasting methods could be generally divided into two broad categories: statistical and intelligent.

Among the statistical techniques, analyzing and predicting bank defaults can be distinguished discriminant analysis (*DA*), maximum likelihood methods such as, for example, logistic regressions (logit), and hazard or duration analysis models. Logit and discriminant analysis are both used for the cross-sectional analyses while hazard or duration models are needed to analyze time series data on bank, corporate or loan defaults.

The main disadvantage of *DA* is that it requires a normal distribution of regressors. The details on the application of *DA* can be found in Karels and Prakash (1987) and Haslem et al. (1992). It is worth noting that the best known multiple discriminant analysis application is proposed by Altman (1968) and Altman et al. (1977). Altman's *Z-score*, or *ZETA* model, combines various financial ratios and attempts to express the probability of a firm going bankrupt.

For the not normal distributed regressors the logit technique can be applied, see, for example, Martin (1977), Kolari et al. (2002) among others.

The details on the usage of duration models for the bank failure prediction can be found in Lane et al. (1986), Shumway (2001), and Molina (2002) among others.

Kumar and Ravi (2007) argue that statistical techniques, as stand-alone, are no longer used in forecasting analysis, but they are frequently accompanied by intelligence techniques for better model performance in predicting bank failures. Among the most common intelligent techniques can be distinguished neural network (*NN*), rough sets (*RS*), case-based reasoning (*CBR*), and other methods.

Kumar and Ravi (2007) conclude that the *NN* is the most widely used technique in the financial forecasting, and it has two main advantages: this model makes no assumptions about the statistical distribution or properties of the data, and it relies on nonlinear approaches. *NN* has its roots from the biological neural networks of the human nervous system. The details of application of *NN* to the bank failures prediction can be found in Tam and Kiang (1992), Chen and Shih (2006), Boyacioglu et al. (2008), and Nachev and Hill (2010) among others.

According to Kumar and Ravi (2007), the second most used intelligent method after the *NN* is *RS* method introduced by Pawlak (1982). This approach is used for the modeling incomplete data. *RS* method is based on the assumption that a chosen for a research object could be approximated by a set of predefined categories, which then can be iteratively analyzed. The application analyses of *RS* for the bank bankruptcy forecasting can be seen in McKee (2000), Slowinski et al. (2005) among others.

Following Kolodner (1993), *CBR* technique is similar to the cognitive process of human beings, which they follow in the problem solving: the solution for the new problem is usually based on the previous similar experience. The popularity of *CBR* can be explained by the fact that it is easy to apply and it provides a good explanation for the output. However the drawback of *CBR* is low prediction performance in general. *CBR* is enhanced by Park and Han (2002), Zhao et al. (2009), and Ahn and Kim (2009) among others.

The varied research is performed to compare different techniques in order to assess, against each other, their ability to predict bank crashes and corporate defaults. For example, Jo et al. (1997), using Korean firms' database, analyze *DA*, *NN*, and *CBR* in order to verify their performance to forecast bankruptcies. They find that *NN* outperforms *DA* and *CBR*, and *DA* outperforms *CBR*. Swicegood and Clark (2001) compare *DA*, *NN* and human judgment in predicting bank failures. They find that *NN* method outperforms other models, considered to comparison, in identifying underperforming banks.

Kumar and Ravi (2007) state that hybrid methods outperform the individually applied techniques and become more popular among the researches. For example, Lin and Chen (2008) propose hybrid approach, compounded from *DA*, *NN*, and logistic regression, in order to predict bankruptcy. They show that this hybrid approach obtains better prediction performance than if used a single approach effectively.

In parallel to the above mentioned efforts, following the seminal works of Black and Scholes (1973) and Merton (1974), the option model of default risk become widely developed and applied to determine the expected default frequency of large corporate entities. These models are based on assumption that a firm, issuing debt to fund its operations, holds, in fact, a valuable default (or repayment) option, which it could exercise (or not) depending on the failure (success) of its investment projects. The limited liability regime limits the borrower´s loss by the amount of equity invested in the firm. Following this thinking, in 1989 Stephen Kealhofer, John McQuown and Oldrich Vasicek founded company *KMV*, which was sold later on in 2002 to Moody's rating agency. The paper on credit valuation by Vasicek (1984) provides details of the approach implemented to monitor creditworthiness of corporate and financial borrowers. This comment finishes a microeconomic part of this sort default model excurse.

***Macroeconomic forecasting techniques***

Demyanyk and Hasan (2009) suggest that micro mode techniques can be more broadly applied in analyses of the financial crises prediction. For example, Kaminsky et al. (1998) propose using macroeconomic factors to forecast currency crises analyzing such information as terms of trade, real interest rate, current account deficit, unemployment rate, *GDP* growth, changes in consumer prices and returns of stock market indices.

Following Neziri (2009), three approaches to predict financial crises can be distinguished in the literature. The first does not focus on the factors that trigger the crises but rather is used to analyze the aftermath of the financial turmoil on the economy, see, for example, Sachs et al. (1996), Hoggarth et al. (2002) among others.

The second is the so called "*signal approach*" which is built on the forecasting technique proposed by Diebold and Rudebusch (1989) for economic indexes and firstly applied to the financial crises by Kaminsky et al. (1998) and then by Kaminsky and Reinhart (1999). This method is used to signal potential crisis when the specific, prior to crises, pattern of individual variables or composite indicators exceed a previously defined threshold. The forecasting research built on this approach can be found, for instance, in Borio and Lowe (2002), Edison (2003), Coudert and Gex (2006), and Borio and Drehmann (2009). As an example of the most recent study based on "*signal approach*" methodology can be cited the research performed by Frankel and Saravelos (2010). They find that the level of reserves in 2007 is a significant leading indicator of the 2008-2009 Global Financial Crisis.

The third approach is employed to evaluate overall effect of explanatory variables on the probability of crises. For example, Kumar et al. (2003), using logit technique, evaluate the overall effect of a set of macroeconomic and financial explanatory variables of 32 emerging countries for a period 15 years and calculate the probability of the crises, assuming values between zero and one. As explanatory variables they use the level of foreign currency reserves, real *GDP*, real effective exchange rate, export volume, ratio of the budget balance to *GDP*, inflation rate, foreign direct investment, portfolio investment amount, and capital account liberalization among others. Kumar et al. (2003) ague the usefulness of logit technique even though it is based on lagged macroeconomic and financial data.

On the other hand, this forecasting technique is widely applied to verify whether the addition of certain macroeconomic variable, constrained by the set of other conventional macroeconomic variables, improve predictive ability of the approaching financial crises. For example, Neziri (2009), using logistic regressions and a panel data sample of 21 emerging market countries, concludes that inclusion of credit default swap (*CDS*) as a factor in the model used to predict financial crises improves the model's forecasting ability, especially in equity market.

Demirguc-Kunt and Detragiache (2005) compare signal and regression models, concluding that the logit regression model is more suitable in order to foresee financial instability. On the other hand, Davis and Karim (2008) find that both models have significant predictive ability, the signal model being better at predicting country-specific crises and the regression model more suitable for detecting global stress.

Complexity and dynamics of the modern financial system and the constant search for the methodology, which could improve the crisis's predictability lead to the appearances of the forecasting approaches based on the intelligent techniques. For example, research performed by Olson and Charles (2003), Clements et al.(2004), and Peltonen (2006) among others, contribute into the investigation of crises forecasting based on the intelligent techniques. Examples of the recent research on the financial crisis prediction, which is based on the application of the intelligent techniques, are the investigation performed by Lin et al. (2008) and Sveshnikov and Bocharnikov (2009).

Lin et al. (2008) use *NN* approach to identify the drivers of currency crises and find that it improves the prediction of crises. Sveshnikov and Bocharnikov (2009) propose the Model of Composite Events Influence to forecast various financial indexes. Their model assumes that the behavior of financial indexes depends on psychological propensity of market participants to buy or to sell the respective financial instruments. Therefore, for forecasting indexes authors estimate the past and the future influence of all topical events on the future sentiments of players to buy or sell.

In a light of unexpected Global Financial Crises the question of the adequacy of forecasting modeling while confronted with alerting techniques arises. For example, Estrada (2009) argues that crisis forecasting models show unstable scenarios in the long run perspective. This is because they are usually focused on the *ex-post* effects of the crash and not on the detecting the nature of crises before its appearances. Consequently, Estrada (2009) proposes an alerting model of approaching crises called "*Multi-Dimensional Graphical Signal Detection Model*" based on the simultaneous usage of mega-surface coordinate system, consisted from numbers of economic variables moving in real time, and multi-dimensional graphical modeling.

#### 2.2.2.2. Alternative Techniques to Predict Financial Crises

The alternative techniques are also used in addition to the discussed above conventional methodologies in order to forecast financial and economic conditions exploiting multidisciplinary approaches.

***Power Law application to financial crashes***

In order to avoid misinterpretations of Power Law applications in the context of this work, it would be useful to figure out the two distinct domains of its use.

First is related to the distributions of statistical parameters described by Power Laws:

the nonnegative random variable $X$ is said to have a Power Law distribution if the following equation is satisfied:

$$PR[X \geq x] \infty (cx)^{-\alpha} \tag{2.2.1}$$

for $c > 0$ and $\alpha > 0$. $\alpha$ is a constant parameter of the distribution known as *exponent* or *scaling parameter*. $c$ is normalization constant. Roughly speaking, in a Power Law distribution asymptotically the tails fall according to the power $\alpha$.

Second domain treats the fitting time series with Power Law based expressions or Power Law patterns in asset prices behavior.

Power Law distributions

Many of quantitative investment researches, such as Markowitz (1952, 1959) and Sharpe (1963, 1964, 1966, 1994, and 1995) etc., are based on Gaussian normal distributions with finite means and variances. Mandelbrot (1963), Fama (1965), Mandelbrot and Hudson (2004) among others, argue against this standard statistical model in finance. They found that in reality asset return distributions have fatter tails than depicted by Gaussian distribution, and therefore normal distribution is in conflict with the real world where the rare event could take place more frequently than it would be concluded out of Gaussian distribution. So this doubt regarding Gaussian capacity to describe reality attracts considerable attention of academics and practitioners attempting to elaborate more precise statistical tools and methodologies.

One of such alternative techniques to forecast crash is Power Law. This law is known as Pareto's (1897) law, named after a famous scientist Pareto, who proposes a thesis that wealth and income distributions obey universal Power Laws. Since then Power Law distributions have become an important part of scientific algorithms as they were providing significant improvement to human understanding of nature and man-made phenomena. For instance, Andriani and McKelvey (2007) present 80 types of extreme happenings described by Power Laws and affirm the necessity of redirection analysis from Gaussian averages to Power Laws distributions.

Briefly characterizing, Power Law distribution is the inverse negative relationship between occasion frequencies and the size of this event.

The rarer event the more considerable magnitude it has and vise versa. This method of data analysis has received a considerable attention from the academicians and applied researches due to its relatively simple mathematical apparatus. Power Law properties are examined by the sizable list of authors such as, for example, Mitzenmacher (2004) and Newman (2005) among others.

Additionally, Calvet and Fisher (2002) confirm the evidence of Power Law properties in time series of Deutsche Mark/ US Dollar exchange rates, five major U.S. stocks and *NASDAQ* equity index.

Baum and McKelvey (2006) also demonstrate the fact of the presence of Power Law distributions in the daily log returns of *Dow Jones* and *NASDAQ* indexes and draw a link between observed Power Laws and non-independent behavior presented in social contexts including stock markets. They study interrelationship between the extreme value theory and Power Law distributions, explaining where Power Laws come from.

One of the interesting applied researches on Power Law distributions was recently published by Zanini (2009). Comparing natural and economic disasters` common features she presents U.S. industrial production swings distribution and distribution of largest U.S. public companies bankruptcies. She suggests that these distributions curves could be described by Power Law expressions.

*Power Law patterns in time series of asset prices*

On the other hand Sornette and Johansen (2001) and Sornette (2003) observe the log-periodic Power Law patterns in prices of financial bubbles leading to a crash. They suggest that the probability for the crisis to happen in the next moment, taking into account that it has not happened yet, could be represented by the following equation:

$$h(t) \approx A + B(t_c - t)^{\beta} + C(t_c - t)^{\beta} \cos(\omega \log(t_c - t) + \phi), \tag{2.2.2}$$

where $A$, $B$, $\beta$, $t_c$, $\omega$, and $\varphi$ are free parameters. Authors argue the usefulness of applications of this technique to predict market crashes by finding the best log-periodic Power Law fit for the observed data series.

Using the approach mentioned above, Johansen and Sornette (2001) identify three crashes on the Hang Seng index during the period 1980 to 1998, in 1987, 1994 and 1997.

Ausloos and Ivanova (2001) observe that Power law along with log-periodic oscillations is useful tool for recognizing preliminary signals of coming crashes. They suggest methods to control or avoid crashes based on this technique.

Zhou and Sornette (2009), analyzing South African stock market behavior, find that one of the important causes of the speculative bubble shaping is positive market feedback, which well quantified by a log-periodic Power Law.

***Phase Transition Theory applied to crises forecast***

In recent years, physicists have started applying concepts and methods of statistical physics to study economic problems. The new era of knowledge with physics approaches applied to investigate economic problems receives the name *Econophysics*, see, for example, Ball (2006), Scalas (2006), and Yegorov (2007) among others. As a particular example, the physicist try to analyze financial market as a complex system under the physics science`s prism. Among many topics in physics there is one the very important in this sense; the Phase Transition Theory, which attracts considerable attention from the theorists and practitioners and becomes nowadays is also applied to studies of economic crashes predictions. In physics it is used to describe transition processes undergone by a natural self-organized system passing from one physical state with stable properties to a different one. For example, Takayasu et al. (2000) finds that features allowing for application of the Phase Transition Theory to economic domains could be observed in the two closely related financial phenomena: balance process of demand and supply and price changes in open markets.

Sornette et al. (1996) analyze behavior of *S&P 500* index before and after the October 1987 crash and propose the Critical Points of Phase Transition Theory as analogs to moments of market crashes or bubble`s bursts. This Critical Point is a singularity point at which a transition of a complex financial system from one state to another occurs, these states being characterized by two different regimes of behavior. An example of such a transition could be a drastic switching from a bubble formation to a financial crash.

By the analogy with the three states of a physical system: solid, liquid and gas, Johansen and Sornette (1999) observe that the individual trader on financial market has only three possible states: selling, buying or waiting. The transformation from this one action to another is continuous process. When individual traders are situated in the "*waiting*" regime, it means that the demand-supply ratio finds itself in a balanced regime and transactions will not lead to the correction in the asset prices. When individual traders receive the positive feedback regarding the market situation from the various trustable sources, they will follow "*buying*" phase and therefore the asset prices increase which lead to the bubble formation. When the negative information arrives to the market, all market participants could make order "to sell" simultaneously which could provoke the bubble implosion and lead to the crash, to the so-called Critical Point of Phase Transition Theory.

Plerou et al. (2003) propose a two-phase behavior model of financial markets, based on the assumption that trading is managed in such a way that demand is characterized by imbalance in the "*sell*" and "*buy*" orders. Authors make analogy between two market phases and two financial market conditions. First is the equilibrium phase, where probabilities of seller-initiated and buyer-initiated transactions are equal and, therefore, prices fluctuate around their equilibrium value. The second phase is out-of-equilibrium phase, when there is no equilibrium in buyers´ and sellers´ orders, which lead to changes in the prevalent "*equilibrium*" price. Plerou et al. (2003) consider that dynamics of interacting market participants in the complex financial system resembled phase transition events in physical systems with many interacting particles. They show how market price volatility could be understood through the phase transitions analysis.

Maslov (2003, 2004, and 2005) develop a new approach to predict financial crises different from traditionally applied by economists, which is also based on Phase Transition Theory. He describes zero-order phase transition in physics and draws analogy of this phenomenon in economy. Zero-order phase transition could be interpreted from the economical point of view as a financial disaster, stock price breakdown, social catastrophe etc. In physics, this event author explains by the assumption that superfluidity can be seen as the motion (movement) of the fluid but not as a thermodynamic state. Fluid becomes viscous under the certain phase transition temperature condition and therefore is not able to penetrate in a thin capillary. Author notices that this point is not a motion (movement), but a state and he calls this point as a zero-order phase transition. In financial market Maslov (2008) explains presence of zero-order phase transition mechanism as follows. There exist periods of time when asset prices go down and the moment comes when nobody trades them by the more expensive price than it was before. Asset holders try to sell their securities at any price and it causes the speculative effect in resale and lead to a price reduction to zero, which is referred as zero-order phase transition. To prevent or postpone zero-order phase transition one should pump liquidity into the system, enabling traders to have an easy access to the money supply. It is not an easy issue as an amount necessary grows as a square of the economic agents to be reached.

***Fourier analysis of time series of financial indexes***

The technique of Fourier analysis attracts considerable attention in diverse scientific fields, and specific needs of the financial economics are not an exception. This method can be characterized as a process of (de)composing analyzed function into simpler pieces. Fourier analysis was originally concerned with representing and analyzing periodic phenomena, via Fourier series, and later was extended those insights to non-periodic phenomena, through the Fourier transform development.

Singh and McAtackney (1998) show in their analysis of future behavior of time-series from physics, astrophysics and finance domains, that Fourier analysis is an important tool for improving the performance of forecasting systems, similar to one introduced by authors in their seminal paper.

Wang (1999) proposes the so-called frequency domain method, which allowed for analyzing behavior of economic and financial time series. Author discovers four types of time series behavior. There are lower, higher, both neither lower nor higher frequency components dominates, and unity at all frequencies. This methodology is based on Fourier transform and it is useful contribution to the methodology of forecast crashes.

Cerny (2003) finds that stock returns, characterized by non-normality behavior, introduce a hedging error even if the hedging is performed optimally. He suggests that hedging strategy is not risk free procedure due to the hedging error. Author also provides an efficient implementation of the hedging error evaluation formula via Fourier transform.

Albanese et al. (2004) propose a technique for the value-at-risk calculation for the models of portfolios characterized by fat tails returns. Their procedure is based on Fourier transformation analysis.

Another example of Fourier analysis application in economic theory is the elaboration of effective method for modeling in the presence of structural change performed by Becker et al. (2006). Their approach is tested on the data of inflation and money demand over the period of 1959-2004. This methodology makes an important contribution to the possibility to reduce the influence of model misspecification.

#### 2.2.2.3. Agnosticism regarding the Possibility to Predict Crises

Along with the varied attempts to foresee financial crises the opinion of the impossibility to predict financial disaster is also presented in the literature.

For example, Fair (2009), analyzing the possible causes of 2008-2009 U.S. recession, derives that this crisis is triggered by the shocked financial variables, such as shocks of the nondurable and durable consumption equations, fall in equity and housing wealth, and drop in export. Author concludes that the behavior of these financial variables is impossible to forecast as the macroeconometric models provide very poor performance on that respect.

Makridakis et al. (2009) find the limited forecast ability in the economy and state that statistical regularity does not mean the possibility of perfect predictability of financial crises. They propose developing emergency plans for a variety of outcomes instead to develop the plans based on the forecasting results.

Taleb (2010), developing the Theory of Black Swan Events, argues that the accurate prediction of future, causal chains of events, including financial crisis, is impossible. Among others factors, he associates the 2007-2009 Global Financial Crises with the inadequacy of diverse statistical methods widely employed in Finance.

### 2.2.3. Flight-to-Quality: Causes and Consequences

The Flight-to-Quality can be defined as an event when investment flies from risky to safe financial instruments, usually represented by U.S. Treasury bonds, leading to a relative growth in the U.S. Treasury bond prices and to a decrease in prices of relatively unsafe instruments. As it always accompanies large-scale financial crises, this phenomenon attracts a considerable scientific interest, especially in the light of the recent Global Financial Crisis.

This section represents the literature review related to Flight-to-Quality studies, divided in the two following parts: the overview of theoretical models considering diverse explanatory mechanisms and, phenomenological investigations focused mostly at empirical features of the Flight-to-Quality events.

#### 2.2.3.1. Theoretical Models

Many mechanisms are proposed to explain Flight-to-Quality and employed in models targeting a better comprehension of its dynamics. Following Caballero and Kurlat (2008), these models are based on diverse factors of different nature such as financial intermediation, rising price volatility, overall risk aversion, tightening of margin constraints, Knightian Uncertainty aversion, pricing power of predominant players and, cooperation of market agents. In spite of the variety of models used to analyze Flight-to-Quality events, there is a common component usually present in these models. This component is a weakness in balance sheets of some market agents. The situation when market participants begin to fear this weakness is also an important issue in a comprehension of Flight-to-Quality phenomena.

***Financial Intermediation Models***

Initially, the term "*Flight-to-Quality*" has been used in the literature, as, for example, in Bernanke et al. (1996), in order to characterize worsening credit conditions during business cycle downturns, especially for borrowers facing significant agency costs of lending. Authors of this paper state that the negative macroeconomic shock reduces the net worth of economically active borrowers. This leads to the sharp increase in agency costs and, therefore, to the limited access for the credit facilities and the further exacerbation of economic downturn.

On the other hand, Holmstrom and Tirole (1997) model financial market equilibrium based on the three types of agents: firms, intermediaries and investors. Their model gives certain insights regarding the role of capital constrains as a plausible cause of a Flight-to-Quality moments. Authors show that in case of credit crunches the spread between intermediated and market debt (direct from investors to firms) increases as a result of poor performance of intermediaries, which, in its turn, leads to the withdrawals and drying up of intermediary capital.

Based on the Holmstrom and Tirole (1997), He and Krishnamurthy (2008, 2009) elaborate the models of direct relationship between intermediaries and investors which explain how intermediation in investment management can trigger Flight-to-Quality. These models are based on the interaction of the non-specialist and the specialist-intermediary investors. Non-specialist could invest directly to the safe assets only and risky investments are performed exclusively through the intermediary, provided by the specific skills to manage risky portfolio, and has the right to invest in both, safe and risky instruments. The dynamics of these agents explain the pro-cyclical behavior of uninformed investors which makes Flight-to-Quality more acute. Intermediary's losses trigger non-specialist investment flight out of risky to the safe assets. This reduces the amount of capital managed by specialist-intermediary and induces him to sell some risky assets. When all the intermediaries encounter themselves in such circumstances, the buyers of risky assets (i.e. the proper intermediaries) become constrained in capital. To force specialist to invest in risky assets, their prices fall. Thus, this model resulting in Flight-to-Quality patterns of market behavior shades a light on why risk premia increases in periods when intermediary institutions suffer losses.

***Volatility and Risk Aversion Models***

Vayanos (2004) proposes the dynamic model, which also rooted in the financial intermediation type of models discussed above, additionally takes into consideration volatility and risk aversion features. He explains the direct relation between the price volatility, illiquidity risk and effective risk aversion. Rising price volatility increases illiquidity risk or liquidity premium and raises costs to liquidate risky assets. This exacerbates risk aversion. In times of high market volatility, the fund managers are concerned about an eventual fall of fund`s performance below a certain limit and, consequently, are worried about a possibility that their clients start to withdraw their money. These managers are concerned about a high volatility scenario also because of the high transaction costs for fund liquidation, as an increase in transaction costs leads to the decrease in their fees. All these concerns cause managers to increase illiquidity premia to prevent fund liquidation. Additionally, it is worth noting that in times of price instability each risky asset added to the fund, increases the likelihood of problems during the fund liquidation. That also leads to an increase in a risk aversion.

Fostel and Geanakoplos (2008) develop a theory of asset pricing under anxious economy conditions, which could be characterized as bad news. The model includes two types of agents: pessimistic, represented by general public and, optimistic investors. They have different view on the asset values and the respective difference is measured by the so-called *liquidity wedge*. Authors define *liquidity wedge* as the spread between the prices, which optimists are willing to pay to borrow funds and pessimists are willing to accept to lend funds. When market is affected by the bad news the *liquidity wedge* increases. Authors also distinguish the two classes of investment assets: those, which could be used as guarantee to gain access to cash and those, which do not have this collateral capacity. Consequently, the increase in *liquidity wedge* reduces prices of assets with poor collateral capacity but the values of assets generally acceptable as loan collaterals increases. Thus Fostel and Geanakoplos (2008) find that Flight-to-Quality happens when liquidity wedge or spread between bid and ask assets prices becomes too high. This model clarifies why under an increased volatility of asset prices, for example, emerging market assets suffer bigger value losses than the similar types of developed economies securities. It also explains why a volatility of emerging assets with low collateral capacity is higher than a volatility of those emerging assets that are more easily accepted as collateral. In the light of this model the Flight-to-Quality could be interpreted as a Flight-to-Liquidity.

***Regulation Constraints Mechanism***

The tightening of margin requirements by regulators is one of the mechanisms used to model Flight-to-Quality event. These models are based on the idea of the possibility of multiple equilibria proposed in the financial panic model of Diamond and Dybvig (1983).

For example, Brunnermeier and Pederson (2009) model the interaction between the speculators and financiers. The speculative traders, limited in capital, sell and buy risky assets, providing liquidity to the asset market. Financiers lend capital to the traders and set margin constraints in order to control their own value at risk. Margin requirement depends on expected market price volatility, which, in equilibrium is a function of the actions of the constrained market agents. Authors call this relation between margins and volatility *margin spiral effect* of leveraged investors. Brunnermeier and Pederson (2009) show that under illiquid crisis equilibrium, when overall riskiness increases and assets volatility rises, the tightening of margin requirements leads to a triggering asset sales and further increases in assets volatility. This implies that the least volatile assets will be subject to lower margin requirements than the risky volatile assets.

Krishnamurthy (2010) proposes a model where the margin requirements play the same role as in the model proposed by Brunnermeier and Pederson (2009). Author concludes that tightening of margin requirements, which are lower for less volatile assets, under high price volatility accentuates the Flight-to-Quality. This happens due to the fact that under such conditions, the investment funds tend to exit from more volatile assets in order to acquire less volatile securities.

### Knightian Uncertainty

Krishnamurthy (2010) also proposes to include Knightian Uncertainty mechanism into his model in order to explain the reason of extreme general fleeing from risky assets into safe assets. He defines Knightian Uncertainty as a concept associated with the risks related to the untested financial innovative instruments and their unexpected behavior during the shocks. Investors do not have conventional, historical track recorded, rules to treat this kind of new financial asset risks. Krishnamurthy (2010) describes two interrelated effects of the increase in Knightian Uncertainty. The first effect is the fall in the asset prices. This could be derived from the investors' uncertainty about the ability of liquidity provider (bank) with limited liquidity to meet its commitments under the shock conditions. Another origin of the asset prices drop is the uncertainty of the own individual investor's exposure to the aggregate risk. Author explains this through the complexity of the market structure and investment instruments. These both, counterparty risk and lack of knowledge related to the individual exposure to the aggregate risks, are the base for the second effect of the increases in Knightian Uncertainty. This is the growth of the liquidity importance as, in time of shocks, the uncertainty triggers an increase in demand for safe investment contracts. Krishnamurthy (2010) also argues that financial crises are usually accompanied not so much by the aggregate lack of liquidity, but rather by liquidity redistribution among the financial agents resulting in a Flight-to Quality.

Previously, Easley and O'Hara (2005) also advocated the importance of Knightian Uncertainty in the analysis of Flight-to-Quality events. Authors treat Knightian Uncertainty as a circumstance when stock market participants lack the information to make precise probabilistic judgment regarding future distributions of risky assets' returns. Easley and O'Hara (2005) interpret this shortage of knowledge as a difficulty of an inexperienced investor to reliably access possible dispersion in future results of his investments. Authors propose a model consisting of two types of agents: risk-averse experienced investors and ambiguity-averse inexperienced investors. Investment assets are represented by safe (cash) and risky instruments. Risk-averse investors have common views on the return distributions and seek to maximize their standard expected utility function over the normal return distributions. Ambiguity-averse agents do not have prior knowledge of the return distributions and seek to maximize their minimum expected utility evaluating each possible return distribution. Authors, based on a worst-case scenario of uncertainty-averse investors, derive that such an uncertainty aversion affects the equilibrium risk premium through its influence on the participation of investors in stock markets.

Similar to Easley and O'Hara (2005), Routledge and Zin (2009) develop a microstructure model of asset trade, analyzing worst-case scenarios in order to explore the connection between Knightian Uncertainty and market liquidity. The lack of latter, they claim, could, in some occasions, trigger Flight-to-Quality events. This model is enhanced by the following assumptions. First, any chosen monopolist market maker is governed by the decision rules aimed to protect him against a worst-case scenario. Second, he sets up bid and ask prices for his proprietary security in order to tradeoff the current and future income of this security against the probability of attracting trade. Authors show that ambiguity about the future security's cash flow leads to the market-maker's uncertainty regarding the impacts on the trading of his proprietary investment instrument. Consequently, this market-maker's uncertainty causes him to increase bid-ask spreads which is followed by the liquidity reduction. Routledge and Zin (2009) explain Flight-to-Quality using the assumption of the aversion towards Knightian Uncertainty that leads to the decreased volumes of trading and reduced market liquidity.

Brock and Mansky (2011) analyze the role of Knightian Uncertainty within their model of risky loans market. They define Flight-to-Quality as the occurrences when lenders fly to safe investments instead of investing in risky projects of borrowers. Knightian Uncertainty is defined as a lack of knowledge how to interpret an unexpected shock that causes a decrease in the borrowers' productivity and consequently reduces loan returns in comparison with the period of time before this shock. When lenders face an unexpected shock they have the three following decision rules at their disposal. The first is to follow the common standard view on a possibility of repayment, which is based on the available knowledge. The second is to maximize payoffs under the worst possible repayment scenario. The third rule is to minimize the maximum possible losses. Authors calculate that an increase of loan prices and a reduction in amount of loans, which is the Flight-to-Quality effect, can be greater under the second and third rules being followed after an unanticipated shock. Their analysis suggests that in credit markets the investor´s ambiguity is not necessarily the primary driving force behind a "*flight to safety*". In these markets the cause provoking a flight to safety appears to be an increased lender's pessimism about the return of lending.

On the other hand, Caballero and Krishnamurthy (2008) argue that Knightian Uncertainty can originate Flight-to-Quality events. Their study is focused on links between financial crises and Knightian Uncertainty. Knightian Uncertainty is incorporated into the model as an agents' ambiguity regarding the probability of being hit either by the first wave of a liquidity shock or being practically not affected by the first wave and hit by the second one. Modeled agents are identical and they issue insurance contracts to each other in order to protect themselves in the period of either first or second liquidity shocks by transferring cash to those in need of it. Caballero and Krishnamurthy (2008) show that under certain conditions investors prefer to accumulate cash instead of issuing insurance contracts against the first wave of liquidity shock because of their fear to be affected by the second wave of the liquidity shock. Such kind of investors' reaction on Knightian Uncertainty conditions, when agents hoard liquidity instead of insuring each other against the liquidity stresses can exacerbate illiquidity and provoke Flight-to-Quality events. This lack of mutual protection of the players in the stressed market can also result in an opportunism or explicit predatory behavior.

***Pricing power of predominant players and their predatory behavior***

Brunnermeier and Pedersen (2005) propose a model of predatory trading which can partly explain why, under Flight to Quality conditions, prices of risky and illiquid assets decrease more sharply than otherwise could be estimated without taking into account the pricing power of predatory traders. Authors distinguish the two types of investments: riskless bonds and risky assets. Their model also considers two types of agents. The first is represented by the large strategic traders seeking to maximize their expected profit and having the impact on the equilibrium price. The second type is the long-term investors, which characterized as small price-taker investors without professional skills and access to the information in order to evaluate the future changes in asset prices. Their demand for the investment instruments is a function of the current asset price. Brunnermeier and Pedersen (2005) model a situation when a big trader is distressed and needs to sell some of his risky assets. This sale in its turn will cause the price of these assets to fall. This information becomes available for other not distressed large traders and they start to sell the same kind of risky assets as fast as possible, which will induce the prices to fall even more sharply, in order to buy back these investment instruments at a lower price later on. So, the market becomes illiquid when liquidity is most required. Authors show that a predatory trader profits from triggering another trader's crisis and that such a crisis can result in contagion across traders and across markets.

Carlin et al. (2007) also develop a model in order to analyze the role of a predatory behavior in episodic liquidity crises. Their dynamic model is similar in some aspects to Brunnermeier and Pedersen (2005) but has some different assumptions and enhancements. Carlin et al. (2007) incorporate a temporary phase of a predatory behavior, inherent to strategic traders, into the cooperative trading periods within which traders provide liquidity to each other. This cooperative period is broken down when strategic traders see an opportunity of super profiting and cause shortage of liquidity allowing for its realization. This is an example of a predatory behavior of big not distressed agents. Predatory traders, selling risky assets quickly at the beginning of the period, cause a decrease in the prices of risky assets and make distressed players even much weaker as they should sell their assets by a fire price. Following the pricing equation proposed by Carlin et al. (2007), the price of the asset could be affected by both, the current rate of trading and by the total cumulative quantity traded over time. Authors suggest that the cooperation allows for the trading of large volumes of the asset at more favorable prices diminishing the predatory behavior induced losses. Authors believe that their model allows for an adequate explanation of illiquidity episodes considering the level of predation or cooperation in financial markets as a determinant of available liquidity. They propose to apply equilibrium strategies that involve cooperation across markets and lead to less frequent episodic illiquidity. Nevertheless, Authors acknowledge that such strategies can have negative impact causing contagion when cooperation breaks down.

#### 2.2.3.2. Empirical Features of the Flight-to-Quality Phenomena

Empirical studies of Flight-to-Quality also result in many valuable findings. In accordance with Caballero and Kurlat (2008), empirical analysis related to this phenomenon is systemized as follows. First, Flight-to-Quality causes can be associated with the weaknesses in balance sheets analyses of different market participants, which turn these market agents the victims of the Flight-to-Quality occurrences. Second, examinations of bond and stock price correlations also could help to detect Flight-to-Quality episodes. It is worth noting the special role the U.S. Treasury bonds play during these events. Third, empirical investigations related to the liquidity problem also address Flight-to-Quality observations. Fourth, assessments of some government regulator policies highlight their relationship with Flight-to-Quality events.

***The Quality of Borrowers***

The early empirical studies, which could be applied for the Flight-to-Quality analyses, are focused on measure of the relationship between the economical agents' external debt financing and aggregate illiquidity conditions. For example, Gertler and Gilchrist (1993), analyzing U.S. credit market over the period of 1975-1991, systematize all borrowers into two groups: small low quality and large high quality enterprises. The small borrowers have more costly access to the financial institutions' lending than the large corporations because of their wide difference in the capital stock. Gertler and Gilchrist (1993) find that under the money tightening conditions, lending to the large high quality corporations increase in comparison with the small low quality borrowers, which could be seen as Flight-to-Quality feature.

The similar Flight-to-Quality evidence is observed by Lang and Nakamura (1995) in their study of the U.S. bank loans market from 1979 to 1992. They employ as a quality indicator the percentage of loans made at or below the prime rate + 1%, assuming that the rate within such boundaries is usually applied for the lending of relatively safe high-grade borrowers. While the rate above prime + 1% is usually employed for the riskier low-grade borrowers.

Authors detect that after the money tightening episodes, the share of bank lending at rates below prime + 1% increase while bank loans with rates above this level decrease. Lang and Nakamura (1995) report that Flight-to-Quality has a countercyclical character in bank lending concluding that, based on this evidence, bank lending could be served as a transmission mechanism of monetary policy.

Another indication of Flight-to-Quality in the credit market can be found in Carey et al. (1993). They study the corporate bonds issuance performed by public offering and by private placement in the U.S. over the period of 1935-1992. Private placement could be defined as a debt issue of relatively small-size information-problematic corporate. Larger size well-known borrowers, who intend to issue not complex large amount security, use public market. Authors note that in times of recession private placement volumes decrease in comparison with public debt issue.

Bernanke et al. (1996) also find the evidence of Flight-to-Quality in the U.S. manufacturing firms. They observe that lower-quality borrowers face relatively high agency costs. This means that they are more limited in finance of their projects than higher quality large firms, which could be seen as one of the Flight-to-Quality features. Such difference in agency costs becomes even wider during the periods of recession. Authors show that during economic turmoil such low-grade firms suffer more decrease in their productions and spending than large corporations.

Demirguc-Kunt et al. (2006) observe Flight-to-Quality features examining the impacts of bank crises, happened over the period of 1980-1995 in different countries, on the structure of the banking sector. Their sample includes the bank-level data of all country-members of the *O*rganization for *E*conomic *C*o-operation and *D*evelopment (*OECD*) and some developing economies. The authors find the facts indicating that economic participants, in each country from the sample, leave weaker financial institutions and deposit their funds in healthier high quality banks. Demirguc-Kunt et al. (2006) call this evidence a "*flight-to-safety*" being a clear reflection of the depositors' preferences.

Alfaro et al. (2004) examine the Chilean market of bank credit along the period of 1990-2002. They analyze such variables as annual growth rate of total loans, consumer loans, and commercial loans and their responses to the tightening monetary policy and bank's capitalization requirements. First, authors observed that during monetary constrained time intervals the small banks are affected by the larger decrease of the growth rate of total loans than the large banks. Second, the drop in the growth rate of all types of loans is larger for less liquid banks than for more liquid banks. Third, the decrease in overall aggregate bank's loan supply affects more small firms and households than large corporations. These observations confirm the importance of borrowers' quality level to the forecasting impacts they will suffer during the Flight-to-Quality events.

***Regulation Constraints***

Alfaro et al. (2004), based on their results described above, find out that Flight-to-Quality can also happen as a response on a monetary policy shocks.

Goyenko and Ukhov (2009) also emphasize an indirect impact of monetary policy tightening on the Flight-to-Quality occurrences. They explain this relationship through the liquidity concept. Authors use as a monetary policy indicator the U.S. federal fund rate and nonborrowed reserves, which is the difference between the total U.S. reserves and the borrowed funds through the Federal Reserve Discount Window. Goyenko and Ukhov (2009) find that U.S. Treasury bond illiquidity can be seen as a transmission mechanism of tight monetary policy into the stock market. Particularly their empirical study shows that first, illiquidity in bond market increases when monetary policy is tightening, and second, bond illiquidity causes the increasing stock illiquidity. The last part of chain is consistent with Flight-to-Quality episodes. Goyenko and Ukhov (2009) estimate that this transmission mechanism of monetary policy takes approximately three months to have effect on the stock market while the fixed-income market has considerably quicker response.

On the other hand, Watanabe (2010) analyzes the real estate lending within the bank's loan portfolios in the period of the Japanese asset price bubble in the late 1990s. He observes that under the Basel regulatory minimal requirements for the bank's capital, the banks initiate lending support of low quality borrowers who do not meet their commitments on the debt repayment instead of crediting high quality borrowers. Thereby author observes the opposite to the Flight-to-Quality concept, so called *evergreening*. Watanabe (2010) concludes that *evergreening* takes place in the Japanese credit market because banks fear the increase of the non-performing loans in their portfolio, which have negative impact on their commitment to Basel capital adequacy requirements, and consequently they try to prevent bankruptcy of their unhealthy borrowers.

***Privileged "Safe haven" Position of Banks***

While authors mentioned above perform empirical studies of asset side of firms and banks balance sheets in order to observe Flight-to-Quality features, Gatev and Strahan (2006) analyze the liability side of banks' balance sheets during 1988-2002. They find the evidence that banks take privileged "*safe haven*" position in comparison to other financial agents during short term Flight-to-Quality which could be characterized by the increase in the spread between U.S. Treasury bills and high grade commercial paper. In particular, authors show that during periods of market turmoil, when investors pull out of asset markets and depress prices, banks experience inflows of deposits as investors deposit their funds in the banks, perceived as a "*safe haven*", and a decrease cost of funding (interest rates which should be paid to the depositors). Gatev and Strahan (2006) findings suggest that Flights-to-Quality happen as flights toward banks rather than out of banks. They explain this fact by the banks' advantage to implicit government liquidity insurance.

***Linkage between Bond and Stock performances during Flight-to-Quality***

Another part of empirical studies of Flight-to-Quality is related to the analyses of bond and stock prices and their relationship in times of Flight-to-Quality events.

Such, for example, Gulko (2002), analyzing U.S. bond and stock relationship over the period of 1987-2000, reports that stock and bond correlations change from weakly positive in normal period to strongly negative during stock market crashes which he define as unexpected decrease in U.S. equity prices. Author refers to this occurrence as *decoupling* which could be also seen as Flight-to-Quality evidence when investors, reevaluating the stock market risk, substitute their risky stock asset investments by the safe high-quality U.S. Treasury bond securities.

Considering firm-level, Gonzalo and Olmo (2005) also study the stock and bond prices relationship for the period of 1997-2004, considering two different pairs of financial indexes: the Dow Jones Corporate 02 Years Bond Index (*DJBI02*) versus the Dow Jones Industrial Average (Dow 30 Industrial Stock Price Index (*DJSI*)), and the Dow Jones Corporate 30 Years Bond (*DJBI30*) Index versus the Dow 30 Industrial Stock Price Index. Authors find Flight-to-Quality feature in the *DJBI02* and *DJSI* pair of indexes: bond returns are negatively related to the stock returns in the period of stress. On the other hand, authors find no Flight-to-Quality effect in the *DJBI30* versus *DJSI* pair. Gonzalo and Olmo (2005) explain this fact by the conceptual deference between short term DJBI02 bond and long-term *DJBI30* indexes. *DJBI02* can be considered as safe haven for investors flying from the stressed stock markets while *DJBI30* could be used as an investment instrument for the investors not concerned with the large changes in the stock market prices.

Baur and Lucey (2009) also observe Flight-to-Quality evidence in crisis periods in their empirical analysis of Morgan Stanley Capital International (*MSCI*) stock and bond index returns of the U.S., U.K., Germany, France, Italy, Australia, Canada and Japan along the period of 1994-2006. Authors find that the correlation between stock and bond markets becomes stronger and negative in times of crises. They ascribe this fact for the Flight-to-Quality effect. Additionally Baur and Lucey (2009) analysis show that Flight-to-Quality could happen simultaneously in many counties explaining this by cross-country contagion.

Briere et al. (2008) analyze performance of the government bonds, investment grade corporate bonds, high yield corporate bonds, and equities of the U.S., the Euro zone, Japan and the U.K. Their study confirms that during the crises there is a significant decrease in the correlations between the government bonds and equities and between the government bonds and investment grade bonds. These effects could be attributed to the presence of Flight-to-Quality phenomena. Authors also highlight the importance of the globalization in comparison to the contagion effects in explanation of Flights-to-Quality episodes.

Brocato and Smith (2010), based on the Gulko (2002) decoupling model, analyze the correlation between bond and equity price movements. Their empirical study is focused on flight-to-safety phenomena over the period of 1984-2006. For this purpose, they employ the daily data of long-term U.S. government bond and *S&P 500* index. They find that stock and bond returns are positively correlated for the five days prior to a crash, but they turn statistically negative for the five days subsequent to a crash. Nevertheless, authors preferred not to include the study of the 2008–2009 financial market disruptions, suggesting that investor flight-to-safety behavior is strongly impacted by uncertainty and lack of liquidity, and hence is a special topic for more profound research.

Previously, Hartmann et al. (2004) analyze stock and government bond markets of Germany, France, U.K., U.S., and Japan within the period of 1987-1999 and their linkages.

Authors are focused on whether crises in stock and bond markets happen simultaneously or follow a Flight-to-Quality pattern. They define Flight-to-Quality as an evidence of both, simultaneously happen events: crash in stock market and accompanying it boom in government bond market. Particularly, they consider the evidence of more than 20% decrease in stock prices as a stock market crisis and, more than 8% reduction in bond prices as a bond crash. Hartmann et al. (2004) calculate that 4.6% of U.S., 7.9% of German, 7.7% of French, 8.3% of U.K., and 3.0% of Japanese stock market crashes coincide with a boom in U.S. government bond market while the likelihood of stock market crises matching other non-U.S. bond market booms is much lower. This evidence demonstrates that Flight-to-Quality happens most likely towards U.S. bond market, which is considered safer and more liquid in comparison with other from the study's sample.

***U.S. Treasury and Emerging Market securities in Flight-to-Quality events***

Previously, Bernanke et al. (1996) concluded that usually the U.S. "*pays*" a limited price for the Flight-to-Quality events than other countries do. They explain this fact as a result of the successful U.S. economic policy and U.S. world status as the safest economy.

Eichengreen et al. (2001) find the evidence of Flight-to-Quality out of emerging markets towards to U.S. Treasury securities along the sample covering the period of 1991-1999 during which the three crises Mexican, then Asian and then Russian happened. For the developing countries´ bonds, authors study impacts the crises had on their maturities and issued volumes. Special analysis is performed for the respective spreads over U.S. Treasury bond yields. Authors consider 10 years yield of U.S. Treasury bond and the difference between 10-year and 1-year U.S. Treasury rates as indicators of the international credit market conditions. Eichengreen et al. (2001) make differentiation between the sovereign issues and other public and private bonds. Additionally in their analysis they employ the country credit ratings. Their findings are the following. First, they find that, regarding emerging markets, the Flight-to-Quality mainly affects that country, where it has been originated. Second, authors observe that during the distressed emerging markets, fixed income asset prices decrease leading to the wider spread over U.S. Treasury. Third, the volumes of emerging markets bond issues are also considerably affected by the crises causing the amount of credit available for business dry up. Fourth, maturities exhibit less evidence of Flight-to-Quality impacts. Nevertheless, during Flight-to-Quality there are certain indications of a greater preference for short-term assets instead of long-term instruments.

On the other hand, Caballero and Kurlat (2008) highlight that usually, when the U.S. stock market suffers a downturn, the U.S. bond market usually grew while the probability of coincidence between stock market crashes and non-US bond market booms is very low. Authors observe that usually, under stressed conditions in Emerging Markets, capital flies both from domestic bonds and equities to U.S. Treasury bonds.

Barth et al. (2009) continue empirical study of U.S. Treasury performance within the period of 1998-2008. They analyze the different domestic and foreign yield spreads over U.S. Treasury including Emerging Market sovereign yield spread. Authors find that during crises happened within the sample period spreads are widened because of flight-to-safety and growth demand for Treasury securities.

Dungey et al. (2009) propose Flight-to-Quality model based on two fund manager scenario and find their model supported by empirical evidence based on the observed behavior of U.S. Treasury bonds prices and emerging market equities quotations. Following this approach there is two investment choices to be taken by fund mangers: either to invest in a high-risk instrument or in a safe asset. This choice depends on the traders' assessments of the probability of crisis to happen. Authors consider that there are certain equilibrium conditions under which the stable mixed investment portfolio is not possible and, hence, results in a Flight-to-Quality. Dungey et al. (2009) discuss empirical data, which can support their model. They analyze the performance of U.S. Treasury securities with maturities from 3 months to 10 years and compare it to the performance of different emerging market financial indexes over the period 1994-2005. Dungey et al. (2009) find the evidence of Flights-to-Quality having as their underlying basis the safe haven status of U.S. Treasury bills and bonds. They show that an increase in U.S. Treasury prices can be associated with the high asymmetric volatility in emerging markets and accompanying it decrease in emerging stock prices.

***Assets Liquidity within Flight-to-Quality intervals***

Empirical analyses of nearly equivalent assets highlight the increase of relative importance of liquidity in periods of Flight-to-Quality events.

For example, Longstaff (2004) compare the performance of bonds issued by Resolution Funding Corporation (*Refcorp*) with U.S. Treasury bonds over the period of 1991-2001. As the *Refcorp* is the U.S. government entity with the liabilities guarantied by the U.S. Treasury and has default-free status, author assumes that the *Refcorp* bond's credit risk could be assumed identical to the U.S. Treasury bonds. Author finds the evidence that, despite on the fact of the same risk characteristics inherent in both securities, the *Refcorp* bond yields are higher than the U.S. Treasury bond yields within the analyzed period. Longstaff (2004) referrers this spread as a *flight-to-liquidity* premium and associate it with the three following factors. First is the decrease in the consumer confidence. Second is U.S. Treasury buy-back, which leads to the decrease in its supply. And third factor is related to the increase in the volume of money market mutual funds, which could be assumed as the Flight-to-Quality presence.

Krishnamurthy (2002) also find the evidence of liquidity importance in the Flight-to-Quality periods, analyzing the differences in the spread dynamics of different issues of U.S. Treasury instruments belonging to the same 30 years maturity group over the 1990-2000. These securities are the newly issued “*on-the-run*” 30 year U.S. Treasury bond and the old “*off-the-run*” 30 year U.S. Treasury bond, issued 6 months prior to the “*on-the-run*”. In order to assess the periods of change in liquidity demand, author additionally uses the comparative dynamics of the spread between the yields of 3-month commercial paper, which could be considered as illiquid asset, and 3-month U.S. Treasury bills, which could be seen as one of the most liquid securities. Krishnamurthy (2002) observes the higher spreads on “*off-the-run*” Treasury bonds over “*on-the-run*” Treasury bonds while the spreads between 3-month commercial paper and 3-month U.S. Treasury bills also have been higher. Author finds evidence for the hypothesis stating that investors prefer liquid securities that provide them with exposure to the long-term risk. This hypothesis is consistent with the particularly important observed fact that the changes in preference for liquid assets are correlated to the bond spread. Author also suggests that economic agents´ demand for liquidity increases ahead of downturns but indicates that the proof of this statement requires future research of more historically extended data samples.

Beber et al. (2009) perform empirical analysis comparing importance of the liquidity and the credit quality of fixed income instruments during distress events. Authors argue that, from a theoretical point of view, stressed financial conditions could result either in Flight-to-Quality, or in Flight-to-Liquidity phenomena which could be clearly distinguished according to whether investors flee towards less risky assets or towards more liquid securities. Meanwhile, empirically this distinction between Flight-to-Quality and Flight-to-Liquidity is difficult to perform. Nevertheless to empirically analyze trade-off between credit quality and liquidity, authors employ sovereign debt spreads over *EURIBOR* of ten

Euro zone countries as measure of credit quality and use the respective orders´ flows for assessing liquidity. Beber et al. (2009) utilize this data exploring their finding that Euro government bond market has unique negative relationship between credit quality and liquidity. This important feature allows them to perform the empirical distinction analysis. Additionally, in order to measure the credit qualities for each country, authors use the sovereign credit default swap (*CDS*). They find that investors care both, about credit quality and liquidity; but in times of distress the relative role of liquidity increases. Beber et al. (2009) additionally emphasize that the direction of the flows into or out of sovereign bond market, is almost exclusively determined by liquidity considerations. They claim evidence that the credit quality of a sovereign issuer matters for valuation purposes at normal market conditions, but in turbulent times investors mainly seek higher liquidity of their sovereign instruments. Authors also note that as their analysis is bounded by specific asset class, it would not necessarily have the same results if the analysis across diverse asset classes is performed.

Goyenko and Ukhov (2009) go further and perform empirical analysis of liquidity linkage between stock and U.S. Treasury bond markets within the period of 1962-2003. They find the evidence that the effect of stock illiquidity on bond illiquidity is consistent with Flight-to-Quality and Flight-to-Liquidity episodes. Particularly, they observe that the change in the illiquidity of stock market creates the conditions for the illiquidity in bond market and vice versa. Authors also give a special importance to the analysis of bond illiquidity for different maturities. They report that short-term bonds have stronger effect on the stock illiquidity with the comparison with middle and long-term bonds' influences.

Goyenko and Sarkissian (2009) study the illiquidity of U.S. Treasury bond with short-term maturity as a proxy for the Flight-to-Quality and Flight-to-Liquidity events and assess their impacts on global asset valuation. Authors operate with the cross-sectional data from 23 developed and 23 emerging markets along the time interval of 1977-2006. Their main conclusions, associated with the Flight-to-Quality, could be systemized as follows. Global shifts in asset allocation strategies from less liquid to more liquid assets as well as from riskier to safer securities increase the flight-to-liquidity risk and flight-to-quality risk, respectively. The flight-to-liquidity/quality risk results in an economically and statistically significant premium across both developed and emerging countries. Their important finding concerns also the evidence, which proves that the U.S. Treasury bond illiquidity could be employed as a predictor of stock market illiquidity around the world. The higher is the absolute value of sensitivity of a country's equity prices to the increase in the U.S. Treasury bond illiquidity, the higher is the expected return of these equities.

Naes et al. (2011) find the evidence that the liquidity tightening along the business cycle could be related to Flight-to-Quality episodes in the periods of economic turmoil. Authors analyze the Norwegian equity market data within the period of 1980-2008 and observe the tendency of coincidence between the liquidity variations and the almost simultaneous changes in the composition of all Norwegian investment portfolios. Particularly, Naes et al. (2011) detect that liquidity conditions of small stocks worsen as investors move towards large stocks decreasing their positions in the small stocks, which could be seen as Flight-to-Quality event. Authors also perform their analysis for the U.S. Equity market within the period of 1947-2008 and obtain similar results. Additionally, based on their empirical findings associated with Flight-to-Quality evidence, authors conclude that the small firms liquidity data have more predictable power of economic future than the large firms, as the former are most affected by the liquidity variation along the business cycle.

## 2.3. Interest Rate Hedge Strategies for Fixed-Income Investment Portfolios

Hedge strategies allow individuals and companies to mitigate risks. This means that they make it more likely that risks are borne by those best able to bear them. This makes it possible for individuals and companies to take on more risky and hence more profitable projects, and therefore create more wealth by hedging those risks that can be hedged. Especially this concerns hedging interest rate risks. This leads to a more productive economy and to greater economic welfare. As an example one can transform the fixed rate funding into variable rate funding and vice versa with a help of such a hedging instrument as an interest rate swap.

Concerning Flight-to-Quality events, they are associated with investors flying from the riskiness of diverse assets towards risk-free investment instruments. At such conditions, the latter experience temporarily exaggerated growth of returns while risky securities suffer from value destruction. Flight-to-Quality episodes could be seen as manifestations of downside risk embedded in investment portfolios. Thus, it becomes important not only to have a fair selection of portfolio assets, but also to make appropriate choices of techniques to protect or to hedge a portfolio against its value destruction due to eventual adverse changes in the relevant risk factors.

In particular, this part is meant to survey a literature related to the interest rate risk hedging. Numerous interest rate hedge strategies can be potentially applied in order to mitigate the negative consequences for the investment portfolio with their origins in interest rate risk, i.e. adverse fluctuations of interest rates. The vast existing literature covering interest rate risk hedging can be divided into two groups: the first dedicated to the static hedge strategies and, the second addressing the dynamic hedge methods.

A static hedge is one that does not need to be re-balanced as a price or other characteristics such as volatility of the securities it hedges change. A static hedge is likely not to last indefinitely. Most hedged portfolios contain securities that will expire or mature. At that point the hedge will need to be adjusted or re-constructed. Unlike a dynamic hedge requiring continuous readjustments, this happens occasionally at comparatively long intervals.

## 2.3.1. Static Hedge Techniques

Unexpected interest rate variations negatively impacting investment portfolio performance represent the very nature of an interest rate risk. A static interest rate hedge strategy could be defined as a mechanism to protect investment portfolio against the adverse interest rate fluctuations which does not need to be re-adjusted as security characteristics and market conditions become different: the hedge scheme is set up initially and almost never balanced. Static interest rate hedge strategy could also be referred to as *hedge-and-forget strategy*.

The two basic approaches to statics hedge, namely exact matching (or dedication approach) and immunization procedures can be distinguished and discussed below. The advanced financial engineering techniques play also considerable role in the development of more sophisticated static hedge mechanisms as well as in their application in the setting up diverse interest rate hedging strategies.

### 2.3.1.1. Exact Matching Approach

Following Elton et al. (2009), dedication or exact matching interest rate hedge technique could be defined as the most conservative strategy which allows matching cash inflows of investment portfolio with its outflows. In accordance with the Leibowitz's (1986a) and Leibowitz's (1986b) analyses of the role of the dedicated portfolio in a pension fund, the idea of exact matching approach implies that pension fund has a set of future liabilities and, in order to meet liabilities' commitments, pension fund needs to construct asset portfolio with cash flows that will match this liability stream. The goal is to create a portfolio, which has capacity to generate sufficient inflows in advance of each scheduled payment in order to be ensured that the payment will be met.

Reilly and Brown (2008) suggest employing zero-coupon Treasury bond as hedge instrument, which could exactly match each liability. Zero-coupon bonds, also called discount bond or deep discount bond, are represented by a variety of forms such as U.S. Treasury bills, U.S. savings bonds, etc. They provide single cash payment on a specific date. Zero-coupon bonds have duration equal to the bond's time to maturity. Therefore, a discount bond could be a time scale precise instrument to offset the interest rate risk.

While exact matching approach has such advantage as simplicity it has some strong disadvantages. Fabozzi (2008) notes that dedication technique cannot protect complex bonds or derivatives as well as can over-hedge investment portfolio. Application of this strategy also implies considerably high costs.

#### 2.3.1.2. Immunization Procedures

The next step in hedge techniques development is related to the immunization procedures. The initial research in this field is undertaken by Samuelson (1945), Redington (1952), and Wallas (1960). For example, Redington (1952) applies the term "*immunization*" to "*signify the investment of the assets in such a way that the existing business is immune to a general change in the rate of interest*". These authors conclude that immunization depends on duration, defined as a weighted average maturity of asset/ liability side cash flows, more precisely interest rate risk is minimized when the duration of the assets and liabilities are equal.

The idea of duration is elaborated independently by Macaulay (1938) and Hicks (1939). In these works, duration is estimated assuming a constant yield to calculate the discount factors. The conceptual difference between these two treatments of duration is that Macaulay (1938) describes it as a weighted average maturity with weighting based on the present value of each cash flow divided by the price, while Hicks (1939) is considering duration to be a measure of bond price elasticity in respect to a change in the bond's yield to maturity. The assumption of duration measure proposed by these two authors is based on an approximate linear relationship between the bond price and the yield change. The first application of this duration concept to the immunization problem solution was done by Samuelson (1945). Later, Ingersoll et al. (1978) show that it works only for flat yield curves and parallel shifts in the yield curve.

Fisher and Weil (1971) propose another approach to duration measure relaxing the assumption of constant yield. They derive duration from the current term structure and it allowed not assuming a flat yield curve and therefore provided an accurate hedging strategy for parallel shifts.

Cox et al. (1979) go further. They state that the duration models under assumption of linear relationship between bond prices and interest rates are valid for little fluctuations of interest rate. However, it is not the case for large changes in the yield due to convex relationship between the price of bond and its yield. In accordance to Yawitz (1989) and Sullivan and Kiggins (1989) this leads to the estimation errors, which can be explained by the effect of convexity. Formally, convexity can be defined as the second derivative of price with respect to yield, or the first derivative of duration with respect to yield. Cox et al. (1979)

introduce the term of stochastic duration, which allows accounting for more complicated changes in interest rates. Their stochastic duration measure is attained by taking the partial derivative of the bond price with respect to the spot rate (stochastic factor) and dividing it by the bond price. Stochastic duration accommodates multiple interest rate shocks for both shape and location changes in the yield curve. Later on Cox et al. (1985) propose the model, which assumes three factors of yield curve changes: height, slope, and curvature.

The significant improvements to the traditional duration-convexity hedging models in the face of stochastic process risk are made by Fong and Vasicek (1983, 1984). They propose so-called M-square hedging model which requires two risk measures for hedging against non-parallel yield curve shifts: duration and M-square. Generally, M-square is based on the linear transformation of convexity.

Unlike M-square interest rate risk model, M-absolute model introduced by Nawalkha and Chambers (1996) needs only one risk measure for the purpose of interest rate risk hedging. Authors define M-absolute measure of a bond portfolio as the weighted average of the absolute distances between cash flow maturities and the planning horizon of the portfolio. Although M-absolute hedging methodology allows immunizing only partially against the level shifts of the yield curve, this technique also diminishes the risks caused by the changes in the slope and the curvature of the yield curve among others risks related to the interest rate term structure shape parameters.

Further enhancements in the immunization performance appear with the development of the duration vector and M-vector models. In accordance with duration vector model, derived by Chambers et al. (1988) and Diebold et al. (2006) among others, the shape parameters (height, slope, curvature, etc.) of the term structure of interest rates are described by a polynomial function. The duration vector of a portfolio of bonds can be obtained by taking a weighted average of the duration vectors of individual bonds.

M-vector methodologies proposed by Nawalkha and Chambers (1997) and Nawalkha et al. (2003) among others represent more general derivation to the duration vector models and do not restrict the term structure of interest rates by polynomial function.

In parallel to the above mentioned developments the so-called key rate duration model is introduced by Ho (1992). The basic idea of this technique could be summarized as the measure of sensitivity of the investment portfolio value to the key spot rates at different point along the term structure of interest rates. Author proposes eleven key rate durations in order to achieve effective level of interest rate risk hedging.

The detailed description of the interest rate risk hedging models mentioned above could be found in Nawalkha et al. (2005). It is also worth noting that many of these hedging models are applicable in dynamic hedge approaches too.

#### 2.3.1.3. Advanced Hedging Mechanisms

Significant increase in the level and volatility of interest rates in the late 1970s and throughout the 1980s led to the process known as an advanced financial engineering. Valuable interest rate hedging tools have been widely elaborated since then in order to be applied to the hedge strategies. Generally hedging instruments could be systemized into the two types. The first is related to the simple financial debt instruments such as Variable Rate Notes and Inverse Floaters among others. The second type is represented by the derivatives, such as interest rate futures, interest rate swaps, interest rate options, etc. Their general characteristics are discussed below.

For the first time, the *V*ariable *R*ate *N*otes (*VRN*) had been issued in 1979. They provide coupon interest at a rate that varies with a specific short-term interest rate, for example, one month Libor. One of the first academic researches dedicated to *VRN* is performed by Cox et al. (1980). Further *VRN* properties are investigated by Chance (1983). Morgan (1986) examines the interest rate risk characteristics of floating rate securities whose rate can change only at particular points in time.

Inverse Floaters, also known as yield curve notes, firstly appeared in 1986 and represent a more sophisticated kind of *VRN*. Inverse Floaters pay interest at a rate that varies inversely with short-term interest rate. This means that it pays high coupon rates when interest rates are low and low coupon rates when interest rates are high. Therefore the price of yield curve notes is much more sensitive to changes in interest rates than a price of a fixed-coupon bond with the same maturity. Ogden (1987) demonstrates that the interest rate risk of a yield curve note is approximately twice as great as that of a fixed-rate note with identical maturity. He also proves that this unique risk characteristic of Inverse Floaters makes them useful in advanced interest rate risk hedge strategies.

In accordance with Ederington (1979), an interest rate futures market was firmly established in 1975. The future contract can be defined as an agreement to purchase (long position) or sell (short position) a specific asset at a certain price in a fixed date. The most popular interest rate futures contracts are represented by Treasury bills, notes, bonds, and Eurodollar futures. The use of interest rate futures contracts as an interest rate hedging strategy receives a considerable attention in the financial literature. Following Kolb and Overdahl (2006) hedging with interest rate futures could be generally divided into three groups: anticipatory hedge, cross hedge, and price sensitivity hedging approach. These types of protection mechanisms have its roots in the exact matching, duration and convexity hedging concepts.

Chance and Brooks (2010) define anticipatory hedge as a protection of a transaction against the interest rate fluctuation that could occur in the future. Anticipatory hedge, as well as other forms of hedging, also includes two concepts such as short and long hedging. The short hedge is based on taking up a short futures position while owning the underlying security to be delivered. If the security price falls, the gain in the value of the short futures position is supposed to counterbalance the decrease in value from the sale of the underlying asset. The long hedge results in taking up a long futures position. If the underlying security price rises, the increase in the value of the long futures position offsets the increase in purchasing costs. In both cases investor locks-in certain interest rate through the futures trading, which he will apply in the future for his transaction. Under static hedge conditions the anticipatory hedge is simplified in a way that the spot and futures contracts are of the same maturity, yield, coupon, and the period of hedge matches the futures instruments perfectly. The cash flows between the spot and futures are also matched.

In accordance with Kolb and Overdahl (2006) the cross hedge is employed when the interest rate risk of certain type of asset is hedged by the investment instrument which differs from the hedged security in respect to the risk level, coupon, maturity, and the hedging period. The usefulness of this method in order to protect investments with the interest rate futures is shown by Ederington (1979) who evaluates the effectiveness of *G*overnment *N*ational *M*ortgage *A*ssociation (*GNMA*) certificates and Treasury bill futures as instruments for hedging price risks related to the spot market transactions. Based on the portfolio theory concepts through hedging the spot position with futures, author determines a minimum-variance hedge ratio. He formulates the optimum hedge by minimizing the one-period risk of the hedge portfolio using the least-square regression approach.

Highlighting that hedging models based on the regression analysis have several drawbacks, Kolb and Chiang (1981, 1982) and Gay and Kolb (1983) propose the price sensitivity approach. In particular, Kolb and Chiang (1981, 1982) propose the hedge strategy, which is based on the matching between the price sensitivity of a bond portfolio and corresponding position with the futures market of equal sensitivity.

Gay and Kolb (1983) develop price sensitivity hedging model, which is based on bond duration and the futures contracts. Interest rate futures are employed to hedge one unit of a bond conditioned by the objective that the hedger's wealth is unchanged over the life of hedge. Gay and Kolb (1983) emphasized that a price sensitivity hedging model is able to capture the key factors necessary to effectively control interest rate risk. These factors are the maturity of the hedged and hedging instrument, the coupon structure of the hedged and hedging instruments, the effective maturity of the hedge, and the term structure of interest rates.

Like futures contracts, swaps are also applied for the interest rate risk hedging based on the exact matching, duration and convexity approaches. Interest rate swaps market, established in the early 1980s and since then having experienced a continuous growth. Bicksler and Chen (1986) define interest rate swap as "*an agreement between two parties to exchange a series of interest payments without exchanging the underlying debt. In a typical fixed/ floating rate swap, the first party promises to pay to the second at designated intervals a stipulated amount of interest calculated at a fixed rate on the "notional principal"; the second party promises to pay to the first at the same intervals a floating amount of interest on the notional principle calculated according to a floating-rate index*".

Balsam and Kim (2001) perform empirical analysis of whether the interest rate swap could be employed for the hedging purpose. They find that in a 5-year period from the swap initiation the swap-users from the sample decrease cash flow variance in comparison with the non-users.

Hull (2008) highlights that interest rate swap has comparative advantage as an interest rate hedge instrument. Swap gives the opportunity for the financial managers to transform the economic characteristics of their liabilities. For example, it could be used to transform a fixed-rate loan into a floating-rate loan and visa versa.

Lesne (2010) specify another advantage of the employment of interest rate swaps associated with investors' ability matching more closely the overall yield curve exposure of their bond investments.

The *plain-vanilla* interest rate options are also important interest rate derivative instruments, which can be systemized into options on futures, caps, floors and swaptions. They are widely used to hedge bond portfolios exposure against the adverse movements in interest rates. According to Martellini et al. (2003), corporate bonds are usually contained so-called embedded options for the hedging purpose. Interest rate option markets are amongst the largest and most liquid option markets in the world today, with daily trading volumes of trillions of U.S. dollars.

As interest rate option prices vary with interest rates they are suitable for implementation of the interest rate hedge strategies. Thus, yield-based calls/puts can be used to hedge the value of a bond portfolio against rising/decreasing interest rates. By purchasing yield-based calls investments can be protected against large losses without sacrificing participation in portfolio appreciation. Still certain negative impacts could come from the cost of the call options.

In respect to the pricing of interest rate options it is worth mentioning a few recent studies. For example, Gupta and Subrahmanyam (2005) analyze pricing and hedging performance of interest rate options. Empirical research in this area has lagged behind theoretical advances partly due to the difficulty in obtaining data. The important contributions of the authors is that their research fills in this empirical gap performing extensive empirical tests of the pricing and hedging accuracy of term structure models in the interest rate cap and floor markets.

Kuo et al. (2007), trying to answer which interest rate option model is more precise and accurate, compare Black's (1976) model, an extension of Black and Scholes (1973) model, with three types of Heath et al. (1992) models specified with different implied volatility functions. Empirical performance in terms of their predicting option prices is investigated using Eurodollar futures and options prices across strike prices and maturities for the period from January 2000 to December 2002. The Kuo et al. (2007) results suggest that a correctly estimate Black's model is the most robust and resilient in predicting option prices within the considered samples while compared to alternatively considered models.

Addressing still small but increasingly significant risk of inflation due to the monetary responses of the U.S. to prevent an economic crisis, Nawalkha and Soto (2009) analyze the models used to hedge large nonparallel yield curve shifts, such as M-absolute/ M-square models, duration vector/ M-vector models, key rate duration models, and principal component duration models. Authors conclude that the mentioned above hedging methods could be also applied to protect fixed income derivatives against the interest rate fluctuations. Nawalkha and Soto (2009) suggest that such extensions could be based on the employment of securities with embedded options.

This work is also important in a sense that it considers a statistical technique called the *P*rincipal *C*omponent *A*nalyses *(PCA)* in order to capture the past changes in the yield curve and to project them into the near future. Following the authors' research, *PCA* model is based on the three main components related to the height, the slope, and the curvature of the yield curve. Although this model has certain drawbacks, it represents an important link to the practical implementation of the dynamic hedge strategies.

## 2.3.2. Dynamic Hedge Rules

A dynamic hedge is a portfolio protection mechanism that needs to be re-adjusted as the price and other characteristics of the investment portfolio or security it hedges changes in order to mitigate the downside risk. In a contrast to a static hedge, the problematic about dynamic hedging is that it requires multiple re-balancing hedge positions as market conditions and/or asset values always undergo changes.

Although if not performed properly, the dynamic hedging of interest rate risk can bring additional riskiness to the hedged portfolio, when designed correctly it can be fairly beneficial for a bond portfolio, especially during the periods when prices of hedging positions and hedged securities move in one direction during Flight-to-Quality and crisis events.

Dynamic hedge of investment portfolios against the interest rate fluctuations is relatively new filed for academic research but this subject becomes considerably popular in light of the recent financial turmoil accompanied by multiple Flight-to-Quality episodes presenting the "*risk-on*" / "*risk-off*" dynamics.

Dynamic hedging schemes are mostly based on the previous model developments made in the field of static hedge approaches. Generally, dynamic hedge strategies can be systemized into the two following areas. The first group of dynamic hedge schemes addresses dynamic variations in price of a proper security which through an adequate dynamic strategy to rebalance the required resulting hedging exposure on the corresponding liability side. This kind of dynamic hedge is not always directly related to the interest rate risk and can be named as a dynamic hedge based on security price changes due to other risk factors.

The second group of dynamic hedge approaches uses forecasting methodologies to anticipate an interest rate behavior and results in dynamically changing strategies of liabilities management based on relevant investment decision-making processes concerning the rules to increase or decrease the coverage ratio of hedge. These hedge techniques depend on a robustness of forecasting mechanisms for interest rate dynamics. This kind of dynamic hedge is often called a time-varying hedge ratio strategy.

### 2.3.2.1. Dynamic Hedge for Changes in Security Value

As it is already mentioned above, the static hedging concepts could be applied in a field of a dynamic hedge. The early research, related to the dynamic hedge developments on a ground of static hedge principles, is performed, for example, by Koutmos and Pericli (1999), Rossi and Zuca (2002), and Sheraz (2006).

In particular, Koutmos and Pericli (1999) propose a dynamic hedge model for *G*overnment *N*ational *A*ssociation *M*ortgage *B*acked *S*ecurities (*GNMA MBSs*) to be hedged by 10-year Treasury note futures. This model provides results superior to the ones obtained with the static hedging strategies. Authors analyze the price fluctuations of *GNMA MBSs* and 10-year Treasury note futures. For this purpose they use the regression approach and error correction parameter from co-integrating relationships included in the conditional mean equations in order to preserve the long-term equilibrium relationship of the two debt securities. Bivariate *G*eneral *A*utoregressive *C*onditional *H*eteroscedastic (*GARCH*) approach is employed with the objective to model time-varying variance-covariance structure of the *GNMA MBSs* and 10-year Treasury note futures. The time-varying variance-covariance matrix generates the dynamic cross-hedge ratios. Koutmos and Pericli (1999) compare the dynamic cross-hedge ratios with the related static hedge parameters in terms of overall risk reduction and expected utility maximization. They find that the dynamic hedge performs better than static even under conditions of the transaction costs incorporated into the analysis.

Rossi and Zuca (2002) develop dynamic hedging strategy for the investment portfolio consisting of the Italian Government Bonds. This fixed income portfolio is hedged by such futures contract as Eurolira and German Bund Futures traded on LIFFE. For this purpose, authors perform the comparison analysis of three interest rate hedging strategies which are based on the duration matching, least squares and asymmetric multivariate *GARCH* concepts. They empirically show that the multivariate *GARCH* hedge ratio outperforms the *OLS* one. Valuation of hedging performance is conducted based on ex-post variance portfolio reduction. In accordance with Rossi and Zuca (2002) the proposed dynamic hedge mechanism allows for more than sufficient potential risk reduction to offset the transaction costs.

Sheraz (2006) perform comparative analysis of hedging performance of constant hedge ratios versus dynamic time varying hedge ratios. For this purpose he analyzes the behavior of both spot and future markets of 10-year U.S. Treasury bonds within the period from January 1993 to December 2002. Author concludes that the time varying hedge ratio outperforms the static hedge ratio in a sense that the former allows minimizing the variance of portfolio returns over the whole period of analysis. Sheraz (2006) also shows that the time-varying hedge ratio provides an efficient approach for bondholders to protect the value of their investments against the interest rate movements by changing positions in both spot and future markets of U.S. Treasuries with the change in actual yields of cash market. Author states that hedging mechanisms need estimates of the correlation between the returns of the hedged and hedging assets. If the correlation and volatility coefficients are changing, then the hedge ratio should be adjusted to account for the most recent information.

In accordance with Martellini et al. (2003) and Hull (2008), in general, dynamic hedge techniques could be represented by the following variety. These are naked and covered hedge positions, stop-loss strategy, so-called *Greek letters* hedge strategies, which include *delta*, *theta*, *gamma*, *vega*, and *rho* hedging.

For example, for equities, the simplest type of the dynamic hedge strategy can be represented by naked and covered hedge positions. The idea of these techniques is the following. Naked position is hold by the investor if he, for example, sells a call option without owning the underlying security. Naked strategy works well if the market asset price is below the strike price at the end of the option maturity. An alternative to a naked position a covered position could be applied. Covered position is hold by the investor if he sells a call option while owning the underlying asset. This strategy benefits if the option is exercised, but in other outcomes it could lead to losses.

Another type of dynamic hedge involves a stop-loss strategy. The idea of this approach is that at the time of investment investor defines the level of losses, which guaranties minimum acceptable asset performance. If the asset value reaches the point below this level this underlying asset should be excluded from the portfolio. The objective of this strategy application to the investment portfolio is a protection against a decrease in value of securities, i.e. to bind the downside risk by pre-setting up the acceptable level of losses at the time when investment is made.

The most sophisticated hedging schemes are represented by the so-called *Greek letters* (although *vega* is not a Greek letter) hedge strategies, which include calculation of *delta*, *theta*, *gamma*, *vega*, and *rho* measures. The choice of the certain Greek hedging mechanism depends on the type of risk factor to be hedged.

*Delta* hedging could be defined as a strategy to diminish the risk associated with the price fluctuations in the underlying portfolio by offsetting long and short positions. The construction of this type of hedge is based on the calculation of the *delta* ratio, which is derived by the relationship between the two price movements: option value and underlying asset price. Mathematically, *delta* can be determined as the partial derivative of the option price with respect to the value of the underlying security. Investment portfolio is referred to as a *delta neutral* when the instantaneous change in the value of the option portfolio for an infinitesimal change in the value of the underlying security is zero. Consequently, keeping delta ratio at zero could be seen as a static *delta* hedge while keeping *delta* close to zero is referred to as a dynamic *delta* hedge. Due to the fact that *delta* changes continuously over time, the hedge should be re-adjusted periodically in order to reset delta measure to zero. This idea is closely related to the Black and Scholes (1973) and Merton (1973) option pricing model. Authors consider complete market conditions with no transaction costs in their model while later on Leland (1985) improves it including transactional costs.

According to Dellinger (2006), the *delta* hedging is useful parameter for small price movements. For larger price fluctuation the *delta* does not accurately reflect the price changes. This leads to another *Greek letter* hedge called *gamma*. *Gamma* parameter describes the amount by which a hedge has to be re-adjusted to stay *delta* neutral. This could be calculated as a second derivative of the option value with respect to the price of the underlying hedged asset. The large in absolute terms *gamma* means that *delta* is highly sensitive to the price of the investment portfolio. *Gamma* hedging reduces the size of each re-hedge and/or increase the time between re-hedges, and thus reduces the costs.

As a proxy for *gamma* hedging parameter the *theta* approach can be used. The *theta* measures the sensitivity of the options portfolio value to the passage of the time.

Following Hull (2008), *delta*, *gamma* and *theta* hedging approaches assume the constant volatility of the hedged underlying asset. The *vega* hedge of the options portfolio is based on the relationship between the value of this portfolio and volatility of the underlying security. *Vega* could be an important mechanism in volatile periods because of its ability to reduce the exposure to volatility on the portfolio.

As an example of the recent advanced research related to the *Greek letters* hedge strategies discussed above could be mentioned the analyses performed by Meindl (2007), Ortiz et al. (2008 ), and Ortiz et al. (2009) among others.

In particular, Meindl (2007) develops the methodology, which can be applied for the dynamic hedging and significantly outperforms the classic Black and Scholes (1973) and Leland (1985) *delta* hedging approaches. Additionally author claims that the proposed methodology can improve the performance of any other hedging methodology by using the two methodologies in conjunction, declaring that when the proposed hedging methodology is used in combination with Black and Scholes (1973) and Leland (1985) methods, it improves their performances. Meindl´s (2007) methodology breaks down the hardly feasible dynamic programming problem into a sequence of smaller problems solved over time, which allows to incorporate changes in the system dynamics and to overcome issues of computational complexity. Consequently, this hedging approach could be employed for the more than one or two underlying assets while many traditional analytic methods usually deal with one or two assets. Author also shows that this methodology can be used under the assumptions of a multi-period horizon, transaction costs, and dynamic asset parameters. Meindl (2007) highlights the future work in this area is desirable as achieved results are based on a set of restrictive assumptions, such as the geometric Brownian motion hypothesis and stochastic volatility, and on empirical *S&P 500* data.

Ortiz et al. (2008) develop a dynamic hedge approach to protect, against the interest rate risk and prepayment risk, the portfolios of *M*ortgage *S*ervicing *R*ights (*MSRs*), which are nothing but fees to be collected by financial institutions to manage mortgages. This is an important research as many financial institutions have significant amounts of *MSR*, which need to be *delta* (dynamic) hedged. The paper develops the *delta*-hedge ratio of *MSR* within a dynamic approach, using three different securities. To lower the cost of the delta hedge, the authors compare three hedge ratios dynamically, in order to obtain the portfolio that needs the least delta hedge. Proposed hedging mechanism is based on the *delta*-hedge ratio rebalancing function which allows readjusting portfolio for changes in market interest and prepayment rates.

Ortiz et al. (2009) elaborate the optimal *delta* hedge model, which allows selecting optimal weights of the securities for the multi-fixed-income investment portfolio at the moment of its initial construction in order the whole portfolio to be *delta* and *gamma* hedged against small interest rate fluctuations. The idea is to define the optimal share of each asset, selecting for the portfolio, such that when the yield is changed, provoking the changes in the asset values, the total value of the portfolio continues to be on the same level. Authors claim that this is feasible as not all securities are positively affected by decreases in rates, but some, such as interest only, *MSRs* or inverse floaters, are negatively affected, at least over a certain range of interest rates. Authors state that the main advantage of the proposed methodology is related to the reduction, but not elimination, of the necessity in the portfolio rebalancing which leads to the reduction of the costs for this operation.

Among possible *Greek* hedging solutions discussed above, *rho*-hedge approach could be useful in dynamic hedging strategies in respect to protect investment portfolios against the changes in interest rates. *Rho* is the rate of change of the price of a portfolio or derivative with respect to the interest rates. This parameter measures the interest rate sensitivity of the individual security or investment portfolio as a whole. *Rho* shows how one percent change in interest rates will influence on the portfolio value. It is usually used in hedging bond portfolios as they usually heavily exposed to interest rate risk.

Dordain et al. (2003) highlight that short and long term *rho*-exposures usually present different behavior. This fact makes hedging process difficult, as the hedging investment portfolio should fit the *rho* parameter of the hedged portfolio maturity by maturity. Authors overcome this obstacle proposing the two following approaches. The first method is based the procedure of decomposition the *rho* parameter of the hedged portfolio in sensitivities to each hedging instruments. The second mechanism is related to the time interval definition and the calculation of term structures of *rho* exposures of the hedged portfolio and the series of hedging instruments.

Thomas and Mare (2007) use the *rho* parameter in order to evaluate the performance of interest rate forecasting approaches involved into the hedging against the long term interest rate risk.

#### 2.3.2.2. Hedging Based on Interest Rate Forecasting

An accurate forecast of the interest rate curve plays a considerable role in the research related to the hedging interest rate sensitive securities represented, for example, by bond portfolios. The comprehensive overview of the major methods employed to predict interest rates is conducted by Fauvel et al. (1999). More recent studies related to the forecasting of interest rate movements are represented by Papageorgiou and Skinner (2002), Bernadell et al. (2005), and Diebold and Li (2006) among others. In particular, Papageorgiou and Skinner (2002) propose the probit model in order to forecast the direction of long-term interest rates. They find that the changes in the forward rates are able to predict interest rate movements one month ahead with more than 60% of success.

Bernadell et al. (2005) develop regime-switching model, which allows generating long term yield curve projections, which depend upon expectations about future macroeconomic scenarios. Authors draw the link between expectations on future key macroeconomic variables and the shape and location of the yield curve. Bernadell et al. (2005) applied their model for the U.S. nominal yield data within the period from 1953 to 2004. They recognize three clearly distinguished yield curve shapes in the analyzed time interval. These are regularly upward sloping, steeply upward sloping curve and flat curve. Bernadell et al.

(2005) demonstrate that their regime-switching model outperforms the results obtained by non-switching model at the time horizon more than 2 years. Authors also state that the proposed interest rate forecasting mechanism could be used as a support tool in the investment process related to the portfolio protection against undesirable interest rate movements.

Diebold and Li (2006) develop a forecasting approach of the term structure of government bond yields at both short and long horizons. They enhance the widely used Nelson and Siegel (1987) model in a dynamic context. This enables them to provide a factor interpretation of the estimated yield curve parameters such as level, slope and curvature. Authors show that the yield curve forecasting of their dynamic method is better for the periods of 1 year ahead.

In accordance with Martellini et al. (2003), portfolio strategies based on interest rate predictions, or market timing strategies, can be distinguished into the three categories: timing bets based on no change in the yield curve, timing bets based on interest rate level, and timing bets based on the specific yield changes, for example, an inversion of the yield curve.

As an example of constructing market timing strategies, Fink et al. (2005) employ the assumption of the optimal time varying hedge ratio in order to analyze the role of term structure variables in the hedging of *m*ortgage-*b*acked *s*ecurities (*MBS*) with Treasury futures. Although the level and slope of yield curve are closely related to the mortgage refinancing, authors show that they are not relevant for calculation of the optimal hedge ratio. They compare the time varying hedge ratio model, which includes these variables with the model, which does not contain them. Author find that these yield curve variables are unimportant in determining the empirically optimal hedge ratio between *MBS* and

Treasury futures contracts as both mentioned above models provide similar out-of-sample hedging results.

Chou et al. (2009) extend the approach of Fink et al. (2005) by employing a more accurate estimation of the yield curve parameters to determine a time-varying hedge ratio. Authors analyze the impact of term structure variables on the hedging performance of the Treasury futures contracts employed to protect *J*apanese *G*overnment *B*onds (*JGBs*) portfolio against the interest rate risk. Chou et al. (2009) incorporate in their analysis some hedging concepts developed by Nelson and Siegel (1987) as well as Kalman filter approach in order to enhance calculations of the optimal time-varying hedge ratio. Following Grewal and Angus (2001), Kalman filter is used for the forecasting future dynamic of interest rates and prices of different assets. Generally, it could be defined as a method, which provides the closest to the true value parameters from the dynamic observations, which contained noise. Chou et al. (2009) empirically find the term structure factors, the earlier time-varying hedge ratio and the current optimal time-varying hedge ratio are closely interrelated: the early hedge ratio and the yield curve affect the next optimal hedge ratio. Although, the time-varying hedge ratio did not provide good out-of-sample hedging effectiveness, the out-of-sample results demonstrate that the performance of the time-varying hedge ratio with term structure variables is better than a hedge ratio with a naive hedge or *OLS* model.

Park and Jei (2010) extend bivariate *GARCH* models, usually used to estimate time-varying hedge ratios transforming them into more flexible ones to analyze the behavior of the optimal conditional hedge ratio. Authors show empirically that the out-of-sample hedging performance is highly related with the variance of the estimated hedge ratios. When hedge ratios are too volatile, meaning that the standard deviations of the estimated hedge ratios are high, the corresponding hedging performance becomes worse. The evidence suggests that bivariate *GARCH* hedging strategies may have only modest improvements when their standard deviations are stable and low enough.

At this stage it is worth making a few comments closing the literature survey presented above. Having been through the evolutionary path of risk perception and diverse approaches related to the downside risks of financial turmoil, the investment activity evolves to develop different techniques to mitigate undesirable outcomes, among which the interest rate risk hedge strategies take a relevant place. In general, still there is a room for further improvement, especially bearing in mind a necessity to reach a better correspondence between the financial models and the underlying reality. In particular, aiming at adequate hedge strategies, it is important to investigate in more detail the phenomenon of Flight-to-Quality, which results in profound impact on possible results of static and dynamic interest rate risk hedge strategies. The next Chapter addresses this issue.

# 3. Flight-to-Quality Model and Analysis

The term Flight-to-Quality is usually used to describe situations in which investors rebalance their portfolios towards less risky investments with the objective to preserve wealth rather than generate it. Investors fly from the riskiness of diverse assets to the quality of safe investments. Consequently, this leads to a relative increase in prices of risk-free securities and to a respective decrease in prices of risky instruments. Usually, under these circumstances, an increase in prices of safe haven assets and a slide in prices of the riskier securities strengthen such investors' behavior further on. Investors continue to withdraw their money from risky investments and fly to the quality of risk-free assets.

Flight-to-Quality events represent an important research subject from diverse points of view. For instance, they augment market instability and make bottom lines of financial institutions more volatile. In addition, these phenomena could also play a considerable role in the comprehension of financial and economic crises, being inseparable components of these larger scale disasters negatively impacting the overall welfare of society.

This Chapter is motivated by the growing demand from academicians and financial practitioners to further develop a comprehension of the nature of Flight-to-Quality events as catalysts of major market disasters. This Chapter is divided into three parts.

The first part describes the methodology of the algorithm proposed for the *ex-post* identification of Flight-to-Quality events. The objective of this identification methodology is to detect the time frames and the strength of the occurred phenomena within the considered historical period, which satisfy the Flight-to-Quality definition, based on the comparison of safe and risky assets performance. The proposed *ex-post* identification methodology is applied further on for the detection of Flights-to-Quality out of risky sovereign Emerging Market bonds towards the safety of U.S. Treasury bonds over the period from January 1998 to December 2010.

The second part is a development of the model capable to describe Flight-to-Quality mechanisms and reveal specific conditions possibly serving as a cause for or coinciding with these events. As previously mentioned, these phenomena are nothing but a significant reduction in the investors' willingness to undertake financial risks. This makes investors fly to quality of safer or risk-free assets. This conceptual decomposition of Flight-to-Quality in terms of investors´ risk attitude serves as a base for the proposed algorithm assessing investors' appetite towards risky assets as well as towards safe securities.

One of the common manners to deal with the risk appetite in economics is to describe it by Arrow-Pratt coefficient named after Arrow (1965) and Pratt (1964). Following Arrow-Pratt coefficient, investors could be distinguished as risk averse, risk neutral and risk lovers towards a given level of risk. But the proposed approach represents an original research, which follows to a widened concept of the risk appetite accounting for risk perceptions, developed by Cochrane (2001), Gai and Vause (2005), and Misina (2005).

In present research, the risk perceptions are taken into consideration through the risk-free interest rate dynamics and studies of its influence on the appetites to hold a chosen basket of assets. Generally speaking, the algorithm of the assessing investors' appetite towards a certain asset class represents an attempt to quantify investors' expectations regarding the future performance of safe and risky securities. An in-deep comprehension of investors´ expectations towards diverse asset classes is very important as it helps understanding the results of collective behavior of investors which could result either into "*irrational exuberance*" of markets, or into panicking and value destruction.

The developed for a generic case approach is further on applied to the quantification of the investors´ expectations towards the risky Emerging Market debt versus the safe U.S.

Treasury bonds for the same time interval as used in the first part to identify historically occurred Flight-to-Quality events, namely, from January 1998 to December 2010. Additionally, the investors´ risk appetite dynamics along this time is researched. The detailed studies of the time behavior of the risk appetite / risk aversion (i.e., willingness/ unwillingness to hold assets) permit to identify circumstances when occurrences of Flight-to-Quality events are expectable.

In the third part the alarm signal system warning of approaching Flights-to-Quality and indicating an end date of each already burst phenomenon is developed. This alarm signal system addresses the modeled investment universe consisting of the Emerging Markets and U.S. Treasury fixed income securities. This system is based on the comparative dynamics of the quantified in the second part investors´ appetites towards safe and risky assets.

Identified on *ex-post* basis, i.e. historically observed, Flights-to-Quality are compared to the respective would-be Flights-to-Quality predicted on *ex-ante* basis. The accuracy of the alarm signal system is investigated as a function of the impact of the events and the subjacent market conditions. The precision of the proposed method is assessed in terms of strength and timeliness of the predicted on *ex-ante* basis events being compared to the really occurred Flights-to-Quality.

## 3.1. Identification of the Flight-to-Quality events

In this section the Flight-to-Quality identification methodology is proposed. In its generic form this approach is applicable to any situation when investors shy away from riskier instruments in pursuit of quality issues with a better creditworthiness. Nevertheless, it is worth noting that there are much more asset classes out of which investors could try to escape than the so-called safe securities suitable for preserving investors´ capitals in turbulent times.

As example of risky assets could be mentioned Emerging Market sovereign debt issues, Emerging Market corporate bonds, Emerging Market equities, Sovereign debt issues of stressed developed countries, corporate equities of the developed economies, High Grade corporate debt, High Yield corporate debt, Junk Bonds, Distressed corporate debt, Commodities, real estate, etc.

U.S. Treasury bonds, British Gilts, German bonds aka bunds, gold, and AAA corporate bonds of the developed economies could be mentioned as widely considered receptors of investment flows originated in Flights-to-Quality. These instruments are usually considered by the investors as safe haven investments.

It is also important to state that what matters it is not only the relative degree of creditworthiness of a set of assets, but the correct identification of the pair of the risky-safe assets involved in a Flight-to-Quality event. It is fundamental to correctly recognize the origination and destination asset classes subjacent to a certain Flight-to-Quality under consideration.

Generally speaking, Flight-to-Quality is always accompanied by the investment flowing out of a certain asset class towards another safer asset class or classes. Restricting the proposed methodology to the simplest case of one-origination and only one-destination domains, this pair of assets should be correctly identified prior to further considerations. Nevertheless, such identification does not represent the subject of the current research, which rather deals with outcomes of widely accepted types of Flights-to-Quality.

Figure 3.1.1 is not exhaustive but presents the most common pairs of assets subjacent to diverse kinds of Flight-to-Quality.

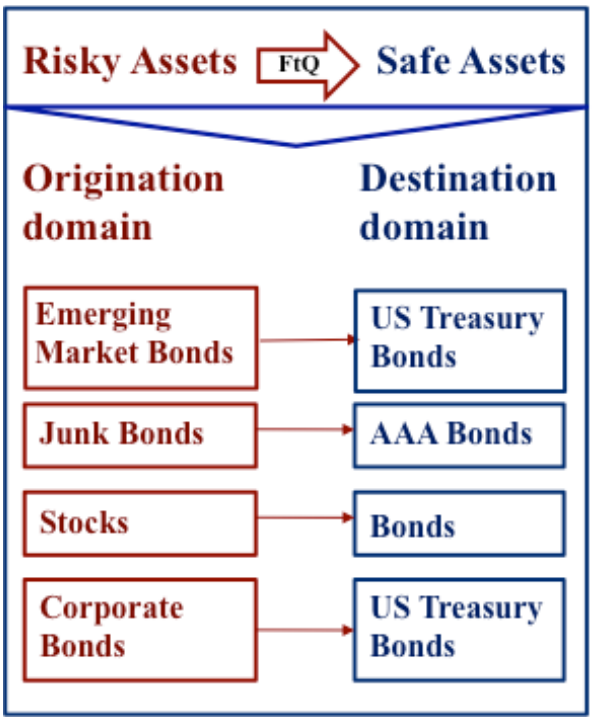



**Figure 3.1.1:** Examples of the most common origination–destination pairs mutually affected during Flight-to-Quality.

In this part the algorithm for identification of the Flights-to-Quality out of risky assets towards the safe securities on *ex-post* basis is proposed. The developed methodology is based on the comparative behavior of total returns of risky versus safe assets. The rational of the total return-based technique resides in the specific characteristics of the total return measure which provides a more precise and complete historic information about investment performance, in comparison, for example, to a price index considered alone.

It is worth noting that this research is focused on the asset performance rather than on credit quality and/or liquidity metrics, which seem to be a case for many other researches in this field. That is why, to the best of my knowledge, the performance addressing metrics of total return is being applied to the Flight-to-Quality identification for the first time. Gauging the comparative performances of risky and safe investment instruments allows for the precise recognition of Flight-to-Quality events.

As the application of the proposed algorithm is focused on the events involving fixed income securities, namely, Emerging Markets sovereign debt and U.S. Treasury bonds, along with the proposed total return-based identification methodology, the complementary spread-based technique is applied for preliminary studies of Flight-to-Quality characteristics. For the fixed income investment domain, the spread-based Flight-to-Quality analysis is based on the differential risky debt issues spread over safe securities yield. The differential spread is nothing, but the difference between the average yield of the portfolio of risky securities and the aggregate yield of the portfolio of the safe bonds. This metrics is widely used in debt-related financial and economic fields of research; see, for example, Barth et al. (2009).

Nevertheless, it should be noted that by construction the spread-based approaches are restricted only to fixed income instruments while the developed here total return-based technique is equally applicable to equities, commodities, etc.

The rest of this part is organized as follows. Firstly, the definition of the Flight-to-Quality is given in terms of the investors′ risk attitudes impacting the total returns of risky and safe assets. Then, the typology of Flight-to-Quality is proposed in terms of the risk-free interest rates dynamics. In line with the adopted definition, the total return-based methodology focused on *ex-post* identification of these episodes is proposed. Secondly, the developed identification algorithm is applied to recognize the time intervals of the Flights-to-Quality out of sovereign Emerging Market bonds to U.S. Treasury securities within the period from January 1998 to December 2010. The obtained results are represented as a function of the impact of the respective phenomena on the difference in performance of the safe U.S. Treasury bonds and the risky Emerging Market debt issues.

### 3.1.1. Methodology of the Identification Algorithm

The total return-based algorithm for the Flight-to-Quality identification is proposed. It is consistent with the developed definition of the phenomena based on the comparative behavior of the total returns of the safe and risky asset classes.

#### 3.1.1.1. Definition of Flight-to-Quality

Prior to propose the working definition of Flight-to-Quality event it is worth making an observation regarding the lack of universal, generally accepted, definition of this kind of episodes, see, for example, Lei (2009). The definition of the Flight-to-Quality event used by diverse authors usually depends on the purpose of their research. For example, Gertler and Gilchrist (1993), Bernanke et al. (1996), and Alfaro et al. (2004) among others study the interdependence between the credit quality of an economical agent and its facility to financing in time of financial turmoil. Authors describe as Flights-to-Quality such situations when lower quality borrowers struggle to obtain finance.

Goyenko and Ukhov (2009) and Naes et al. (2010) among others analyze the liquidity of diverse asset classes and highlight the importance of the liquidity factor in Flight-to-Quality episodes, which also referred to as a Flights-to-Liquidity. Authors define these events as an increase of investors' preferences for the most liquid securities.

The empirical research dedicated to the attempts of disentangling Flight-to-Quality from Flight-to-Liquidity performed by Beber et al. (2009).

Bradley and Taqqu (2005), Baur and Lucey (2009), and Inci et al. (2011) among others, analyzing the correlation between diverse origination-destination markets, define Flight-to-Quality as a situation when the correlation between a chosen pair of markets decreases, while the performance of riskier one drops.

As the present research is focused on assets performance, measured in terms of total returns, and the quantification of the investors' appetite for safe and risky assets, the proposed definition of Flight-to-Quality event is consistent with the purpose of the research.

***Definition*:**

*Flight-to-Quality phenomenon* is referred to as a mass investment migration from risky to safe assets caused by a sudden drop in risk appetite and increase in risk aversion, leading to an underperformance of total returns of risky assets while compared to the total returns of safe assets.

The time frame of Flight-to-Quality event is a rather short time interval when investors´ expectations regarding the future performance of risky securities suddenly deteriorate. Under such conditions market participants aspire to transform their risky assets holdings into safe haven instruments looking to secure the original investment value instead of increasing it. The growing demand for the safe investments benefits their total returns in comparison with the total returns of risky assets.

The choice to use the total return metrics in order to measure the safe and risky assets performance is explained by the following set of considerations.

The total return measure for fixed-income instruments assumes that all coupon payments and redemptions are re-invested by buying more of the same bonds. As coupon payments are included, especially if to look backwards, there are no variations of this measure due to the payments of coupons as they are used to buy more of the same security. This could be not the case for price indexes, as the market value of a bond *ceteris paribus* is supposed to decrease after a bondholder received the coupon payment.

Thus, the total return indexes are used herein as their usage eliminates eventual impacts of coupon payments on the investment performance, which are not related to the perceived riskiness of the assets. As Flight-to-Quality phenomena are not originated out of coupon payments but rather by changes in investors' risk appetite, the possibility to avoid influences not related to risk considerations is very important for the identification purpose. Hence, Flights-to-Quality could be identified with major precision.

#### 3.1.1.2. Typology of Flight-to-Quality

From the phenomenological point of view this research proposes the whole range of Flight-to-Quality phenomena be classified into two categories, depending on the increase or decrease of risk-free interest rates within a chosen episode, resulting respectively in the decrease or increase of the total returns of safe assets.

***1$^{st}$ Type of Flight-to-Quality: FtQ under a decrease in risk-free interest rates***

The first, and the most common, type of Flight-to-Quality is associated with the periods when the risk-free interest rates fall and, consequently, the total return of risk-free assets grows. The two following subtypes of the 1$^{st}$ type of Flight-to-Quality could be distinguished:

*1.A-subtype*: when the total returns of risky assets decrease (due to an increase in interest rates of risky assets);

*1.B-subtype*: when the total returns of risky assets increase, but considerably weaker while compared to the positive performance of safe assets (due to the decrease in interest rates of risky assets which is weaker than the respective decrease in the risk-free interest rates).

***1.A-subtype:*** *the Flight-to-Quality under a decrease in risk-free interest rates, characterized by the positive performance of risk-free assets with the negative performance of risky assets*

This subtype of Flight-to-Quality episode is characterized by a slide in the interest rates of the safe assets with a simultaneous considerable increase in effective risk premiums, due to the well-defined increase in risk aversion.

The risk premium increase, i.e. spread widening ($\Delta$ *spread* > 0), is greater than the absolute value of the decrease in the risk-free interest rates or, in other words, of the decrease in the interest rates of safe assets ($\Delta\, i_{SA}$): $\Delta$ *spread* > abs ($\Delta\, i_{SA}$). This is illustrated in Figure 3.1.2.

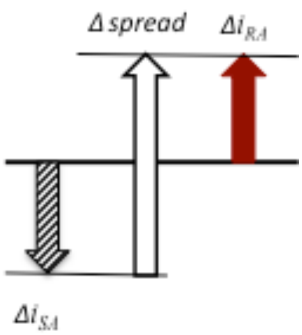



**Figure 3.1.2**: Schematic interest rates dynamics of safe and risky assets under the 1.A-subtype Flight-to-Quality conditions.

As can be seen from the Figure above, the interest rate of risky assets increases ($\Delta\, i_{RA} > 0$) and makes discounted cash flows of risky assets to devalue. Consequently, under such conditions, the predominant mechanism underlying this subtype of Flight-to-Quality is a drop in investors´ appetite for risky assets. The *1.A-subtype* of the analyzed phenomena, occurring under decrease in risk-free interest rates, is schematized in more detail in Figure 3.1.3.

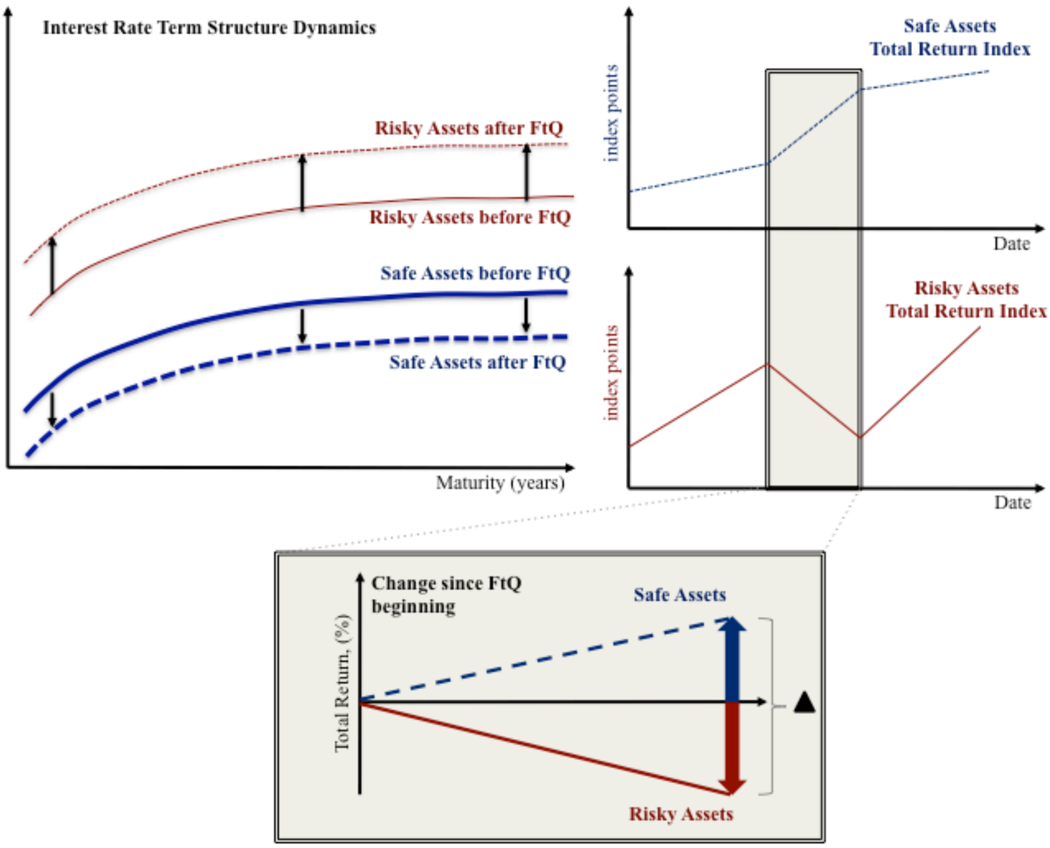



**Figure 3.1.3**: Scheme of the Flight-to-Quality resulting in a positive performance of safe assets and a negative performance of risky assets.

The stylized dynamics of the interest rate term structure for both, safe and risky assets, along with the corresponding dynamics of the respective total return indexes, are depicted at the charts in the upper part of Figure 3.1.3. The Flight-to-Quality window is shadowed. The bottom insert of Figure 3.1.3 illustrates the difference between the safe and risky indexes performances as expressed in percentage of their respective values at the beginning of the considered episode. The final difference is marked by the curly bracket width delta (Δ). It is but the strength of Flight-to-Quality in terms of assets´ returns over the corresponding time interval.

The described above *A*-subtype of Flight-to-Quality event is a widely known and studied in literature, see, for example, Hartmann et al. (2004), Gonzalo and Olmo (2005), Baur and Lucey (2009), and Inci et al. (2011) among others. As it will be evidenced further on, these events can be ascribed to the phases of slowdown in the economic growth and economy contraction.

***1.B-subtype****: the Flight-to-Quality under a decrease in risk-free interest rates, characterized by the positive performance of both, safe and risky assets*

This subtype of Flight-to-Quality event is characterized by the circumstances when both, safe and risky assets total returns grow but the increase in the safe assets total returns outperforms the upside of the total returns of the risky assets.

This kind of phenomena is observed when the drop in risk appetite, i.e. spread widening ($\Delta spread > 0$), is not sufficient to revert the positive effects on risky assets discounted cash flows caused by a slide in risk-free interest rates ($\Delta\ i_{SA}$): $\Delta\ spread <$ abs ($\Delta\ i_{SA}$). This is illustrated in Figure 3.1.4 below.

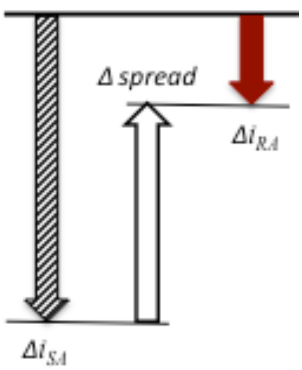



**Figure 3.1.4**: Schematic interest rates dynamics of safe and risky assets under the 1.B-subtype Flight-to-Quality conditions.

Thus, the increase in risk premiums is weaker than the decrease in risk-free interest rates. So, instead of devaluing, seen in the previously described *1.A-subtype* of Flight-to-Quality, the risky assets exhibit positive performance, although weaker than the increase in returns of safe assets. Thus, the interest rate term structure is shifted down for the both classes of assets. The *B*-subtype of Flight-to-Quality is depicted in more detail in Figure 3.1.5 below.

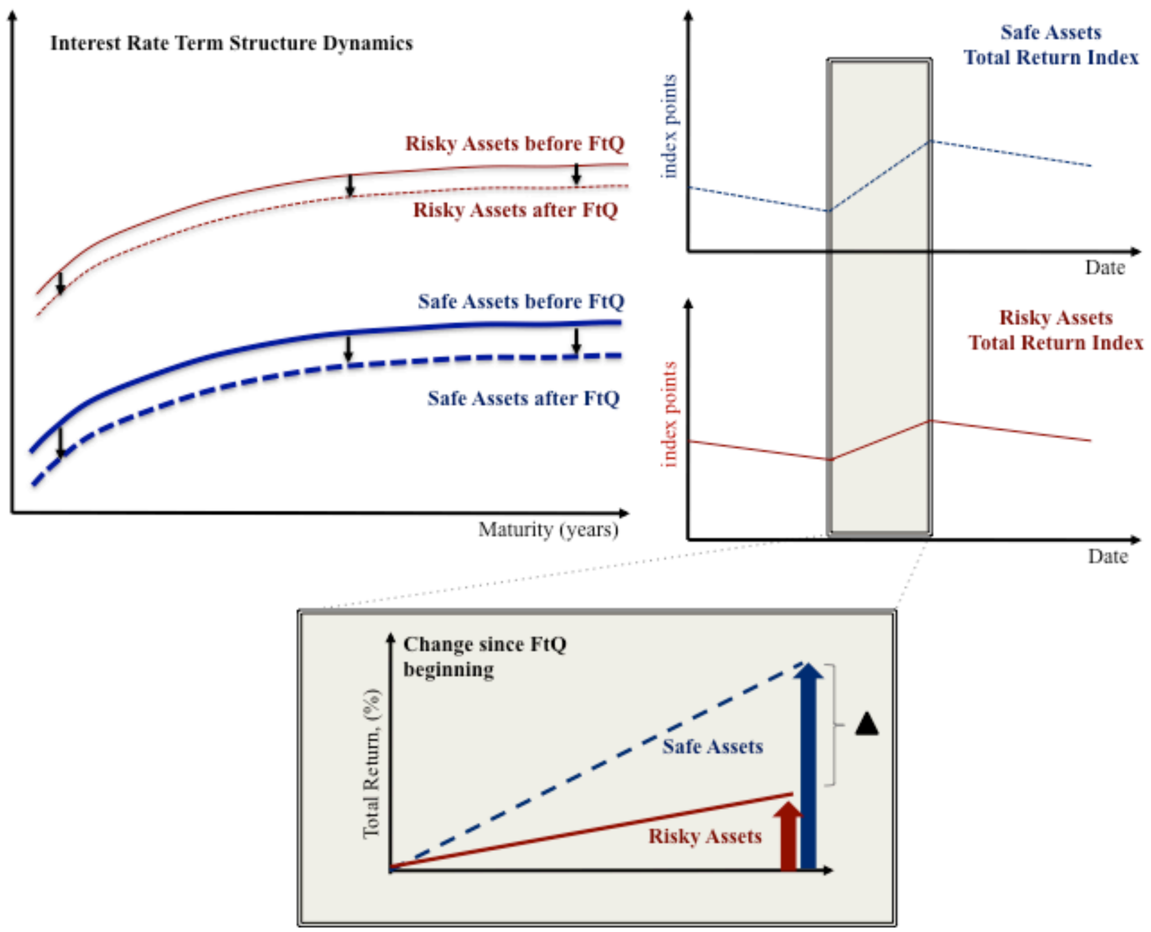



**Figure 3.1.5:** Scheme of the Flight-to-Quality resulting in a positive performance of both, safe and risky assets.

The stylized dynamics of the interest rate term structure for both, safe and risky assets along with the illustrative upward dynamics of their total returns are depicted at the charts in the upper part of Figure 3.1.5. The Flight-to-Quality window is shadowed. The bottom insert of Figure 3.1.5 illustrates the difference between the upside of safe and risky indexes performances as expressed in percentage of their respective values at the beginning of the considered episode. The final difference is marked by the curly bracket width delta (Δ). It is but the strength of Flight-to-Quality in terms of assets´ returns over the corresponding time interval.

It is worth noting that there is a lack in literature regarding diagnostics and analysis of occurrences attributable to the *1.B-subtype* of Flight-to-Quality. As it will be evidenced further on, these events can be ascribed to the initial worries of investors regarding a continuation of economy expansion and slowdown periods. Thus, these events are very important as possible warnings of switching from expansion to slowdown and vice-versa, i.e. indicators of turning points between expansion-slowdown phases of economy.

***2<sup>nd</sup> Type of Flight-to-Quality: FtQ under an increase in risk-free interest rates***

The second type of Flight-to-Quality occurrences is related to the situations when both, the risky assets total returns and the risk-free assets total returns decrease but the total returns of risky assets suffer a considerably higher decrease in comparison with the drop in the total returns of safe assets. These phenomena are likely to accompany phases of the massive withdrawal of the investment from both the safe and risky fixed income securities, causing the generalized decrease in their prices.

This kind of phenomena is observed when, within the Flight-to-Quality window, the risk-free interest rates exhibit an increase ($\Delta\, i_{SA} > 0$), i.e. the risk-free interest rate term structure is effectively shifted up. In this case, the decrease in appetite for risky assets, i.e. spread widening ($\Delta\ spread > 0$), is superposed over the impacts of risk-free interest rates increase. This is schematically depicted in Figure 3.1.6 below.

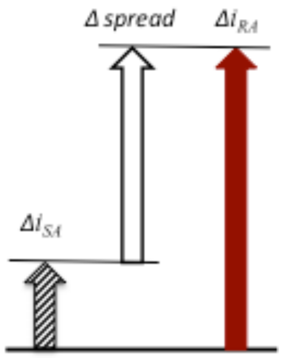



**Figure 3.1.6**: Schematic interest rates dynamics of safe and risky assets under the 2nd type of Flight-to-Quality conditions.

Thus, both factors $\Delta\ i_{SA} > 0$ and $\Delta\ spread > 0$ make the discount factors for risky assets decrease. The second type of Flight-to-Quality is illustrated in more detail in Figure 3.1.7.

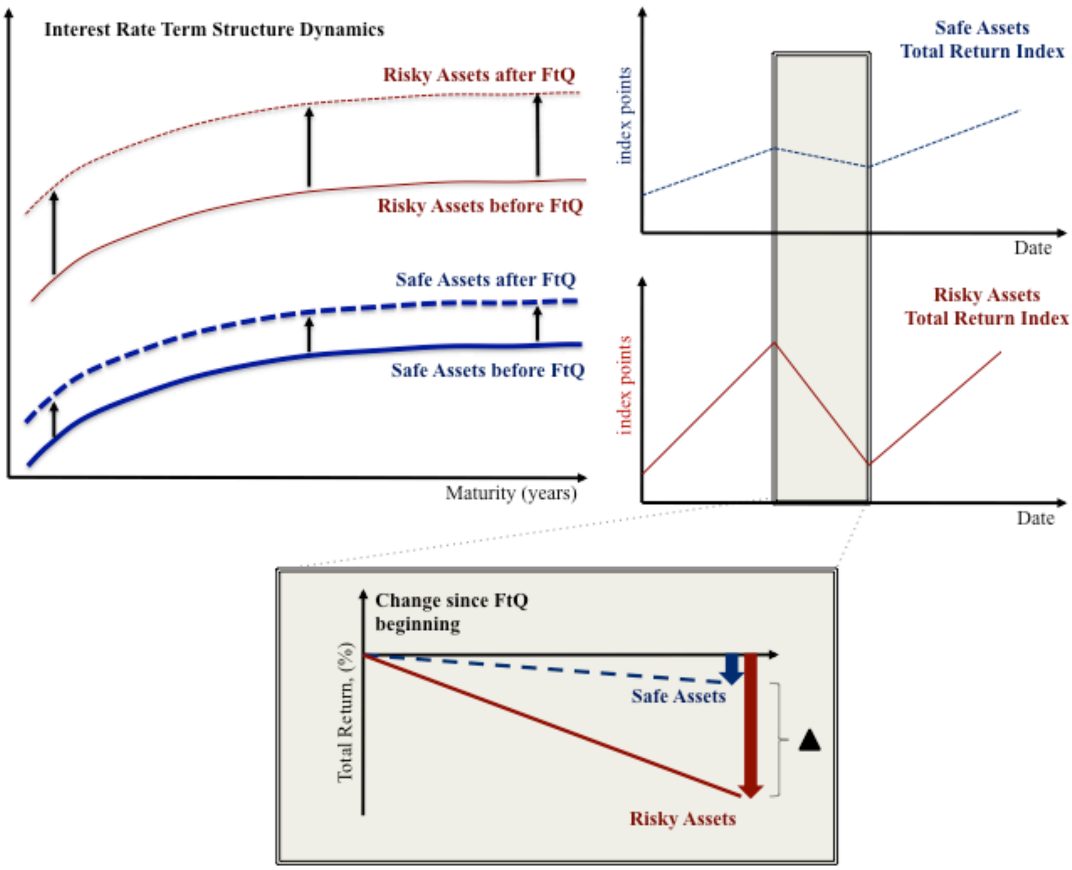



**Figure 3.1.7**: Scheme of the Flight-to-Quality resulting in a negative performance of both, risky and safe assets.

The stylized dynamics of the interest rate term structure for both, safe and risky assets, along with the illustrative downward dynamics of their total returns are depicted at the charts in the upper part of Figure 3.1.7. The Flight-to-Quality window is shadowed. The bottom insert of Figure 3.1.7 illustrates the difference between the downsizes of safe and risky indexes performances as expressed in percentage of their respective values at the beginning of the considered episode. The final difference is marked by the curly bracket width delta (Δ). It is but the strength of Flight-to-Quality in terms of assets´ returns over the corresponding time interval.

The second type of the Flight-to-Quality event is rarely addressed in literature. Nevertheless, in the empirical analysis of the comparative behavior of the Emerging Markets bonds versus U.S. Treasury securities performed by Ross and Bernal (2007), the episodes of the described above 2$^{nd}$ type are classified as a Flight-to-Quality along with the episodes of the *A*-subtype of the 1$^{st}$ type of Flight-to-Quality within the considered therein period of October 2003 – October 2007. It is worth noting that the authors do not call these events as Flight-to-Quality but name them as "*sell-offs*".

As it will be evidenced further on, the 2$^{nd}$ type of Flight-to-Quality events can be ascribed to the phases of economy expansion.

The proposed typology of Flight-to-Quality occurrences is summarized in Table 3.1.1 below. As can be inferred from this Table, the *1.A-subtype* of Flight-to-Quality, under the more pronounced negative or positive changes of the risk-free interest rate, can be transfigured into the two extreme forms: the *1.B-subtype* and the 2$^{nd}$ type of Flight-to-Quality, respectively. In other words, the most commonly occurring *1.A-subtype*, in a typological sense, is located between the two more rarely observed typologies of *1.B-subtype* and the 2nd type.

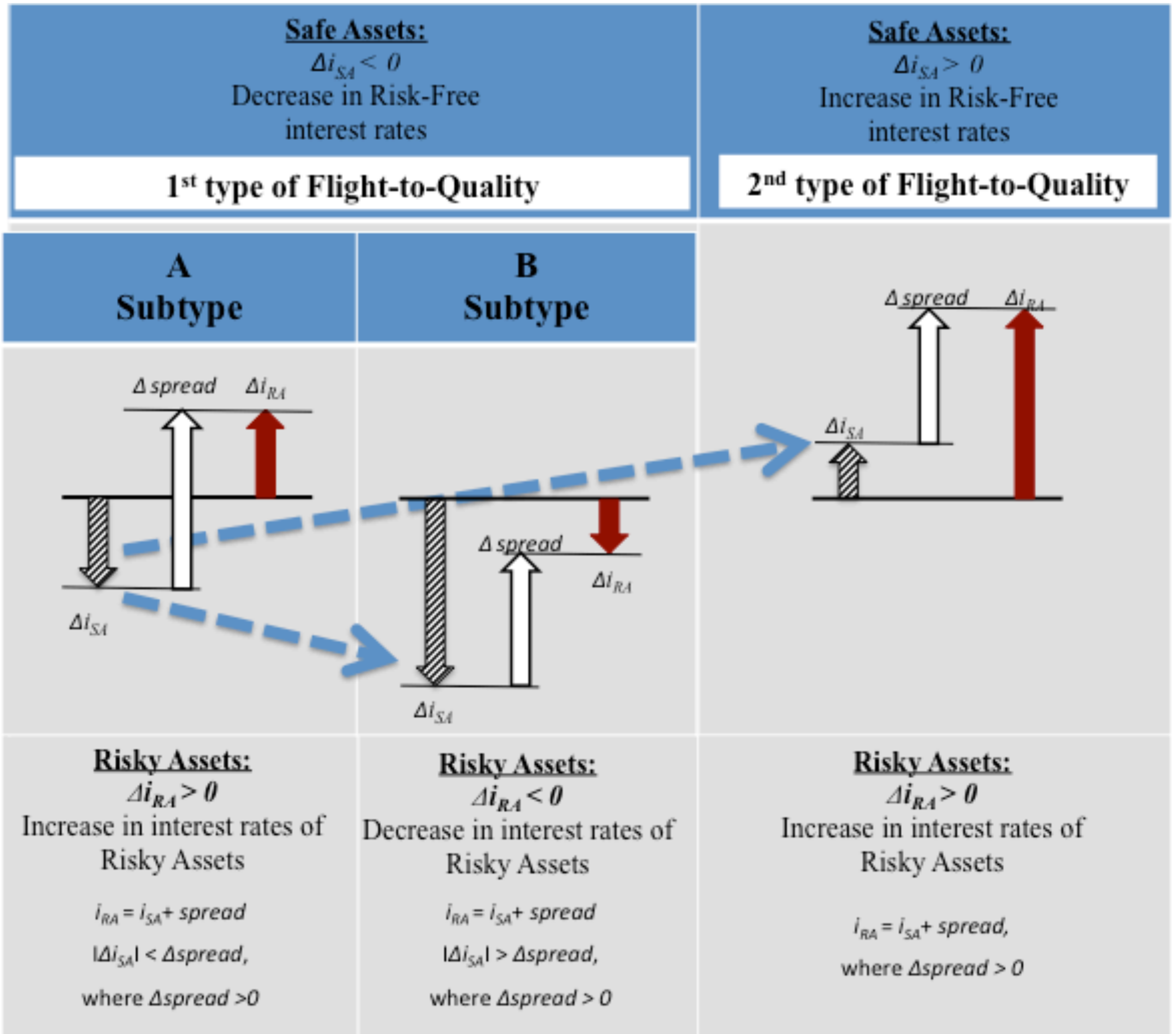



**Table 3.1.1**: Summary of the Flight-to-Quality typology.

It is worth mentioning, that for all the types and subtypes of Flights-to-Quality described above, the strength of the event on the previous Figure 3.1.3, Figure 3.1.5, and Figure 3.1.7 is marked by the curly bracket width delta (Δ). This parameter is but a percentage difference between the safe and risky total return indexes. So, the bigger the differential Δ, the more impactful is the phenomenon.

Thus, one could think of a Flight-to-Quality event as of an increase in a percentage difference delta (Δ) between the safe and risky total return indexes. Hence, on a curve, that one could draw to depict the time behavior of delta (Δ), a final date of a Flight-to-Quality corresponds to the respective local maximum. This insight is used in the next section to develop an automated algorithm to identify final, and then initial, dates of Flights-to-Quality.

#### 3.1.1.3. Total Return-based Technique for Finding Flights-to-Quality

The general concept of the total return-based technique resides in a quantitative difference in the aggregate performance of risky assets, on the one hand, and, on the other, the safe haven securities.

In order to identify Flights-to-Quality, as defined in previous section, the algebraic algorithm, which compares the respective total returns of safe and risky assets, is developed.

The following three steps compose this approach.

***1^st^ Step***

For each rolling anchor date *AD* of a chosen *n*-day long interval, a set of *n* different subjacent sub-intervals is considered; the anchor date (*AD*) is fixed, while the initial dates go from 1 to *n* days back into the past as it is illustrated in Figure 3.1.8.

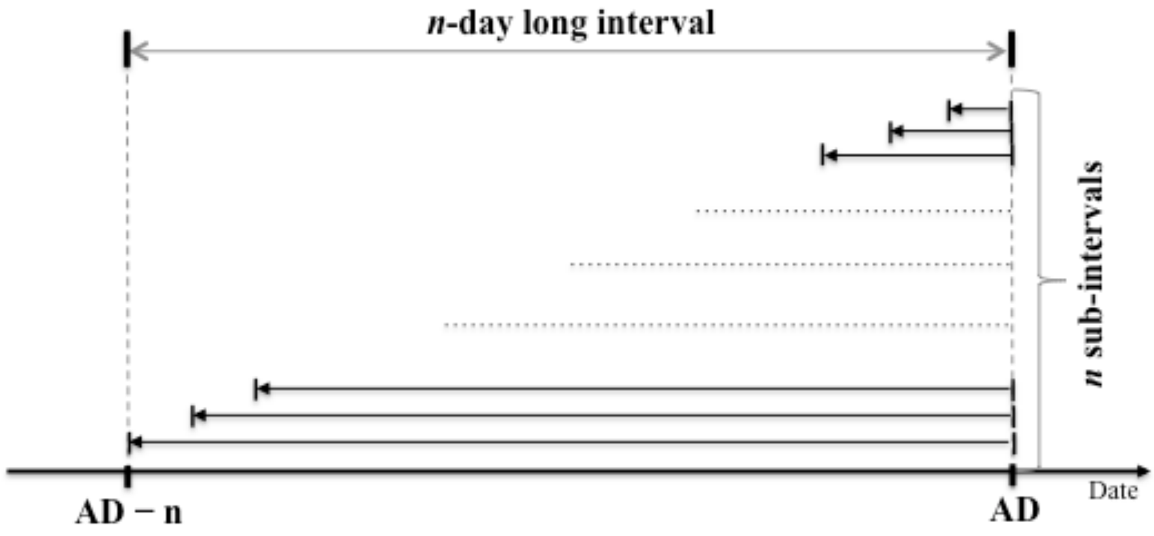



**Figure 3.1.8**: Scheme of the *n*-day long interval and *n* sub-intervals in respect to the anchor date (*AD*).

Then, the *n* values of percentage returns of the risky asset total return index (further on referred to as risky assets index) and the respective *n* values of percentage returns of the safe asset total return index (further on referred to as safe assets index) are calculated. Thus, the *n* different initial dates are employed in the consecutive return calculations using in each turn the same final, or anchor date (*AD*). That means that each time after the rolling anchor date (*AD*) is fixed, the algorithm goes by *1*-day steps into the past until the chosen *n*-day limit, i.e. the date *AD*−*n*, is reached. Thus, the algorithm calculates the percentage returns of safe $R_{(k)}^{S}$ and risky $R_{(k)}^{R}$ assets indexes for each of *n* sub-intervals, $k \in [1, n]$. Hence, for the *k*-day considered asset index return, calculated at the anchor date (*AD*), or, in other words, for the return over the *k* days precedent to the anchor date (*AD*), it is possible to write the following expression:

$$R_{(AD-k,\,AD)}^{Index} = \frac{Index_{(AD)}}{Index_{(AD-k)}} - 1\,, \tag{3.1.1}$$

where *Index* stands for safe (risky) assets index;

$R^{Index}$ is the return of safe (risky) assets index;

*AD* is an anchor date consecutively assuming all the dates within the analyzed historical period;

$k$ is a number of days within which the return of the safe (risky) assets index is calculated. Here $k \in [1, n]$ while $n$ could be thought as the largest analyzed Flight-to-Quality window.

Interpreting the application of the above expression (3.1.1), it is worth noting that for each anchor date (*AD*) this expression is calculated $n$ times for $k \in [1, n]$. This application successively provides the return of the *Index* during the last day, during the two last days, during the three last days, and so on until the limit length of $n$ last days.

***2nd Step***

The $n$ differences between the returns of safe and risky assets indexes ($\Delta R_k$) are to be calculated. This could be expressed by the following formula:

$$\Delta R_{k(AD)} = R^{S}_{(AD-k,\, AD)} - R^{R}_{(AD-k, AD)}, \tag{3.1.2}$$

where $k \in [1, n]$.

The maximum value out of the $n$ values of the return differences between safe and risky assets indexes is to be found. The search for the maximum delta ($\Delta R^{MAX}_{(AD)}$) for each anchor date (*AD*) is performed. I.e., while searching for the maximum delta ($\Delta R^{MAX}_{(AD)}$), the anchor date (*AD*) is fixed and only the length of the subjacent *k*-day long sub-interval varies. This could be written as follows:

$$\Delta R_{(AD)}^{MAX} = \underset{k=1,2,\ldots,n}{MAX}\left(\Delta R_{k(AD)}\right). \tag{3.1.3}$$

In parallel, the number of days ($k$), which corresponds to the found $\Delta R_{(AD)}^{MAX}$, is stored as a parameter $N_{AD}$. It is worth noting that the length of the sub-interval $N_{AD}$, which maximizes the difference in returns for each anchor date ($AD$), is not fixed and varies from one anchor date ($AD$) to the next, and so on. Later on, in the 3rd step of the algorithm, this number ($N_{AD}$) will be used for determining the initial dates of Flight-to-Quality events.

At this stage one can make the anchor date ($AD$) advance day by day. Calculated now for each rolling anchor date ($AD$), the values of $\Delta R_{(AD)}^{MAX}$ (maximized as a function of the parameter $k$ according to the above expression 3.1.3) are used to build the respective curve of maximum differences between safe and risky assets index returns. This curve is schematically represented in Figure 3.1.9 below.

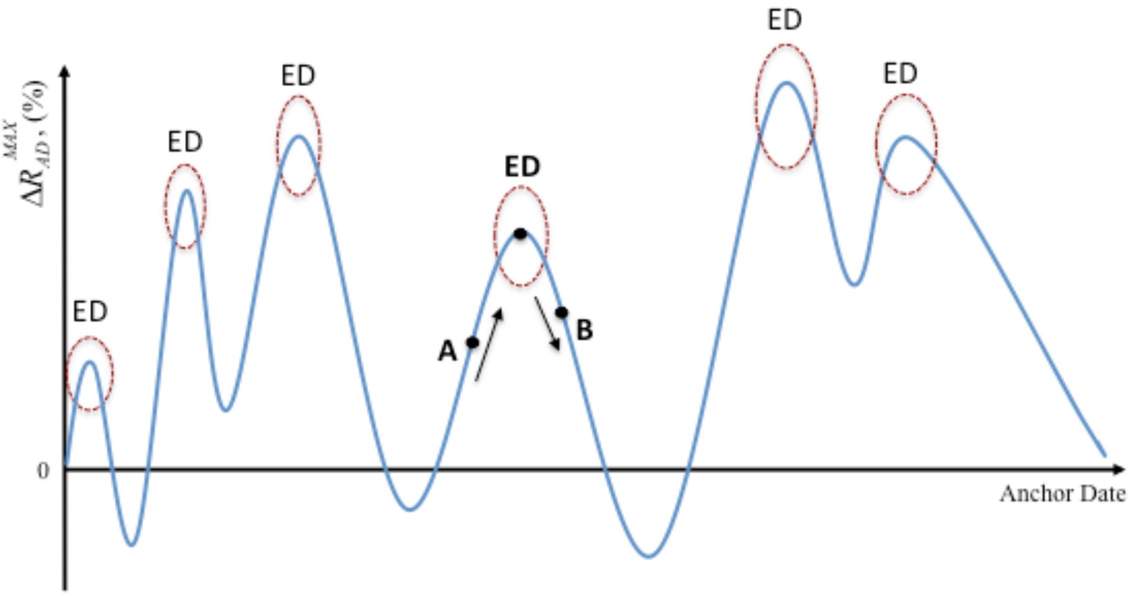



**Figure 3.1.9**: Maximum differences between safe and risky assets total returns in percentage of the initial indexes´ values observed $N_{AD}$ days prior to the anchor date ($AD$).

Abscissa of each point of the curve illustrated in Figure 3.1.9 corresponds to the rolling anchor date (*AD*). In its turn, an ordinate is the maximum difference in returns of safe and risky assets indexes within *n* sub-intervals of the n-day long window. The local maxima of the $\Delta R_{(AD)}^{MAX}$ curve, marked by dashed ovals in Figure 3.1.9, are the end dates *ED* of the Flight-to-Quality events.

This can be comprehended as follows. Prior to a chosen local maximum date, corresponding to the Flight-to-Quality end date (***ED*** in bold), the Flight-to-Quality impact on the total returns difference is strengthening with time; see the point ***A*** in Figure 3.1.9. On the other hand, posterior to the same chosen local maximum date (***ED*** in bold), the difference in the total returns along the time scale is decaying; see the point ***B*** in Figure 3.1.9. That is the reason, why the local maximums of the $\Delta R_{(AD)}^{MAX}$ curve are considered to determine the end dates (*ED*) for the preceding them Flight-to-Quality events. This is what one would expect to observe and what in fact is observed while searching for Flight-to-Quality end dates (*ED*).

Summarizing the second step, firstly for each anchor date (*AD*) and the rolling *n* days long window the maximum ($\Delta R_{(AD)}^{MAX}$) of the *n* differences ($\Delta R_{k(AD)}$) is found. Then the local maxima ($\Delta R_{(ED)}^{MAX}$) of the curve of the maximum differences ($\Delta R_{(AD)}^{MAX}$) are identified, indicating the corresponding end dates (*ED*) of Flights-to-Quality.

***3^rd^ Step***

For the identified end dates (*ED*), the difference ($\Delta R_{(ID,\ ED)}^{MAX}$) is maximized as a function of the initial date of Flight-to-Quality *ID*, which could be explained by the following equation:

$$\Delta R_{ID}^{MAX} = \underset{k=1,2,\ldots,n}{MAX}\left(R_{(ED-k,\,ED)}^{S} - R_{(ED-k,ED)}^{R}\right), \tag{3.1.4}$$

where $ID = ED - k$.

Here the use of end date ($ED$) instead of anchor date ($AD$) means that only the end dates of Flight-to-Quality ($ED$), identified in the previous 2nd step of the algorithm, are employed and not all the rolling anchor dates ($AD$). Using the parameter $N_{AD}$, mentioned in the 2nd step of the algorithm, which is the number of days of Flight-to-Quality event, the initial date ($ID$) is expressed, as follows:

$$ID = ED - N_{ED}\,. \tag{3.1.5}$$

It is worth noting that the initial date ($ID$) corresponds to the calculated at $ED$ maximum of the return difference between the safe and risky assets indexes for each chosen end date ($ED$) of Flight-to-Quality as it is illustrated in Figure 3.1.10 (see point $B$):

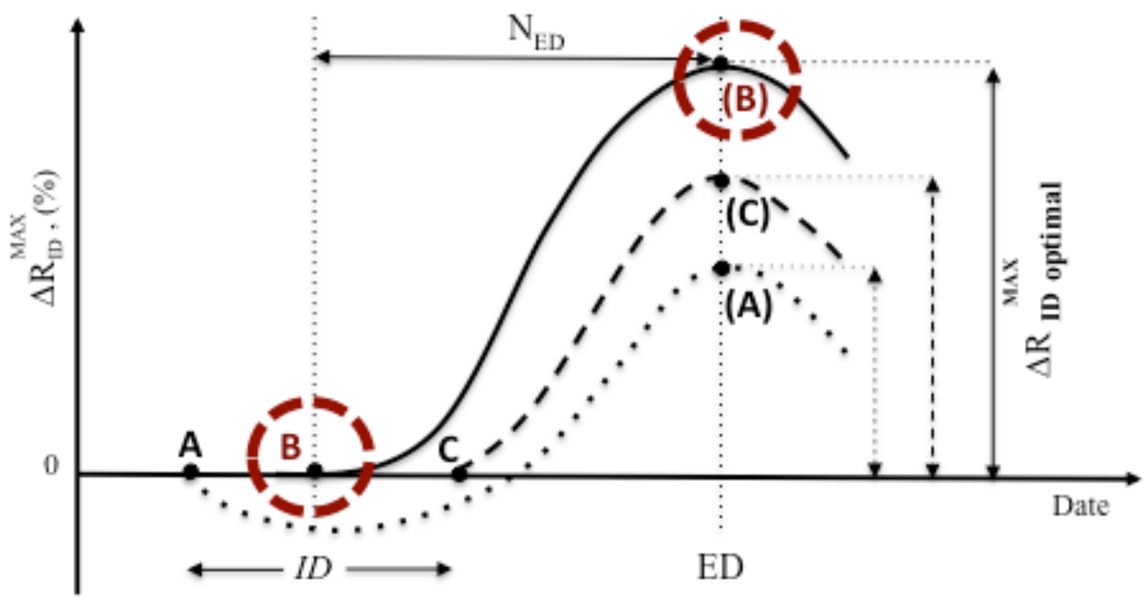



**Figure 3.1.10**: The difference between safe and risky assets total returns in percentage of the initial index values for diverse trial initial dates including the properly defined optimal initial date *ID* (point *B*).

Summarizing the essence of the exposed algorithm one can state that it consists firstly of determining the end date (*ED*) of the Flight-to-Quality event, which corresponds to the local maximum of the safe and risky total return difference of the considered rolling periods, and, secondly, the initial date (*ID*), which corresponds to the maximum difference between safe and risky total returns for the already fixed Flight-to-Quality end date (*ED*). Such an approach arises due to the complexity of the Flight-to-Quality event, which is an increase in the returns´ difference of the two indexes describing safe and risky asset classes.

Regarding the selection process of Flight-to-Quality-like episode to be included in the sample, its end date (*ED*) must present the difference in the safe and risky assets indexes performance superior to a certain pre-defined strength, or event impact parameter (*EIP*). The greater the value of this selection filter criterion, the more impactful are the Flights-to-Quality and the smaller is their number within the considered historical period.

### 3.1.2. Applied Identification Algorithm: Emerging Markets vs. U.S. Treasury bonds

The proposed Flight-to-Quality identification methodology is applied in order to detect the time frames of the flights out of the Emerging Market fixed income securities to the U.S. Treasury debt issues within the period from January 1998 to December 2010. The choice to use these asset classes for the application Flight-to-Quality identification methodology could be explained as follows.

Emerging Markets (*EM*) play a considerable role in the growth of world economy and have a strong influence on the global market conditions. In accordance with the report titled as *The World Economic Outlook* issued by International Monetary Fund (*IMF*) in September

2011, emerging developing countries account for 47.9% of world Gross Domestic Product (*GDP*) and their share in the world export activity is 36.4%. From the mentioned above report it could be concluded that, despite the recent world financial crisis, the emerging economies had shown themselves being resilient, as they had not become stagnated, exhibiting firm rates of growth. Over the period of 2003 - 2007 the annual real *GDP* growth of emerging economies is more than 7.62% on average. In 2008 it equals to 6.0% and in 2009 being affected by crisis becomes 2.8%. Nevertheless, it accelerates to the 7.3% in 2010.

All mentioned above suggests that the *EM* have become one of the main engines of world economic life. *EM* attract investors seeking higher returns but, at the same time, these extra returns are correlated with higher risks. In accordance with Boz (2007) and Loser (2009), analyzing the historical performance of *EM*, the emerging economies can exhibit a vulnerability of returns, which usually leads to the significant changes in investors' confidence. In times of uncertainty, especially during financial turmoil, investors leave their highly volatile *EM* positions and prefer less profitable but safer instruments. The U.S. Treasury (*UST*) bonds become favorite securities in comparison to the *EM* debt issues in such circumstances.

Following Ho and Lee (2004) and Brealey et al. (2007), *UST* bonds are considered to have a worldwide status of the risk-free securities and their generic rates are used as a benchmark for the risk-free interest rates. Mentioned above authors employ *UST* benchmarks as accurate measures of risk-free interest rates in their forecast models.

Analyzing the origins and consequences of financial crises at quite different points in time Bernanke et al. (1996) and Cowen (2009) treat *UST* bonds as safe assets. Studying the Flight-to-Quality events out of *EM* securities, Eichengreen et al. (2001), Caballero and

Kurlat (2008), Barth et al. (2009), and Dungey et al. (2009) also consider *UST* securities as risk-free benchmark instruments.

This section continues with the data description used further on for the application of the proposed total return-based identification methodology for the detection *EM – UST* Flights-to-Quality happened within 1998 - 2010.

**3.1.2.1. Data**

Being focused on Flights-to-Quality out of *EM* bonds towards safety of *UST* securities, the aggregate behavior of *EM* debt is modeled by the J.P. Morgan EMBI-Global index (Bloomberg ticker: *JPEGCOMP* (further on referred as *EMBI*)) while a performance of risk-free securities is described by the *UST* total return index provided by the iBoxx Ltd. (Bloomberg ticker: *ITRROV*) within the period of 13 years from January, 1998 to December, 2010.

Additionally, the J.P. Morgan Emerging Markets Sovereign Debt Spread Index (Bloomberg ticker: *JPEMSOSD*) is employed for preliminary assessment of a time width of the Flight-to-Quality windows.

The values of *EMBI*, *ITRROV* and *JPEMSOSD* indexes are imported from the Thomson Reuters DataStream and the Bloomberg terminals.

***EMBI as a Proxy of Emerging Markets Behavior***

The J.P. Morgan Global Emerging Market Bond Index or EMBI-Global (*EMBI*) tracks total returns for actively traded U.S. dollar denominated debt instruments, including Brady bonds, loans, and Eurobonds, issued by the sovereign and quasi-sovereign institutions belonging to the Emerging Markets economies.

*EMBI* was firstly launched in December 31, 1993 and is available on a daily basis, which is important for the Flight-to-Quality diagnostics also performed herein on a daily basis within the analyzed period.

The *EMBI*'s definition of the *EM* countries, participants in the index, is based on the combination of the two following factors. The first criterion is based on the World Bank income levels classification: the countries are considered as *EM* if their per capita income level is classified as low or middle during at least one of the past three years. According to the World Bank calculations, the low and middle income per capita was upper limited by USD 12,275 in 2010.

The second factor is associated with the country debt-restructuring history. Regardless of their World Bank per capita income level classification, countries are classified as emerging economies if they either have restructured their external or local debt during the past decade or currently restructure their external or local debt.

In accordance with Lee (2011), as for March 31, 2011, these two criteria allow the *EMBI* to have among the index participants the 42 most important countries, that international investors consider being a part of the *EM* universe. The important participants by the market capitalization of the outstanding debt are Mexico, Russia, Brazil, Turkey, Philippines, Indonesia, Venezuela, Colombia, Lebanon, and Peru among others.

Once EM universe is defined, the next 7 mechanisms are used as the brackets criteria for inclusion of the specified country into the *EMBI* participants. These criteria are the issuer type classification, currency denomination, current face amount outstanding, remaining time until maturity, settlement method, quantifiable source of cash flow return, and daily quoted price availability. The *EMBI* contains only the sovereign and quasi-sovereign bond issues from the index eligible countries constrained by a current face amount outstanding of USD 500 million or more with at least 2.5 years until maturity.

The next step in the calculation of the *EMBI* is the definition of the weights the selected emerging countries have. The *EMBI* index weighting methods are based on the traditional approach. The weight of each debt instrument is determined by dividing the issue's market capitalization by the total market capitalization for all the instruments in the index. The result represents the weight of the issue usually expressed as a percentage of the total *EMBI* capitalization. The country weights for the *EMBI* are calculated by aggregating the weights of the debt instruments for each selected country.

The *EMBI* construction methodology explained above makes this index a widely recognized benchmark for the aggregate behavior of the sovereign *EM* debt. For example, Dages et al. (2005) highlight the importance of the *EMBI*. Authors use it as an indicator of the EM economy conditions in their study of *EM* credit derivatives. Jeanneret (2009), Girault (2010) and Butikofer (2010) also employ the *EMBI* for their analyses of *EM* debt. Being calculated in terms of total returns, *EMBI* represents a confident base for gauging aversion to and appetite for investing in emerging countries and, consequently, for the total return-based identification of Flight-to-Quality out of *EM*.

***ITRROV Index as a Proxy of the U.S. Treasuries Total Returns***

The risk-free securities are described by the iBoxx $ Treasuries total return index (further on referred to by its Bloomberg ticker *ITRROV*). As well as the *EMBI*, the *ITRROV* is calculated on a daily basis, which suits the daily basis Flight-to-Quality identifications. The *ITRROV* includes the following UST maturity buckets: the short to medium run 1-3, 3-7, and 7-10 years buckets, and the long run ones of 10-15, 15-25, and 25 and more years. Within the *ITRROV* index, each bond is weighted according to its amount outstanding. The UST bonds should have a minimum time to maturity at issuance of 18 months in order to be included in the index. Extendable bonds whose maturities are extended also require a minimum time to maturity of 18 months from the date of extension. In addition, all bonds must have a remaining time to maturity of at least one year on a rebalancing day.

Being calculated in term of total returns, the *ITRROV* index represents a perfect measure for safe investment instruments' behavior needed to perform the total return-based identification of flights out of the risky *EM* to the safe *UST* assets. There are two following considerations to be taken into account. The first is related to the fact that the *ITRROV* is by construction concentrated in sovereign debt issued by the U.S. government, which comprises 100% of the index. The second inference is based on the widely accepted safe haven status of the U.S. whose importance continues to grow especially in comparison to the recent turbulences in the Euro zone countries sovereign debt. It should be noted that recently, on August 5, 2011, rating agency Standard & Poor's had downgraded the AAA U.S. rating to AA+, but even though the safe haven status of *UST* in fact was not affected.

***JPEMSOSD Index – EM vs. UST Comparative Sovereign Riskiness***

The differential *EM* spread could be defined as the spread between the aggregated yield of the *EM* sovereign debt issues and the aggregated yield of the *UST* basket with similar maturity patterns. The wider the spread, the riskier is the *EM* debt as it corresponds to the greater additional yield premium demanded by investors to hold this *EM* debt. Thus, a Flight-to-Quality event could be characterized by widening *EM* spread over *UST* yield.

As a proxy for the differential *EM* spread, the J.P. Morgan Emerging Markets Sovereign Debt Spread Index is utilized herein, and further on referred to by its Bloomberg ticker *JPEMSOSD*. This index is available on a daily basis since December 31, 1997, which suits for the purpose of the Flight-to-Quality identification analysis also performed herein on a daily basis.

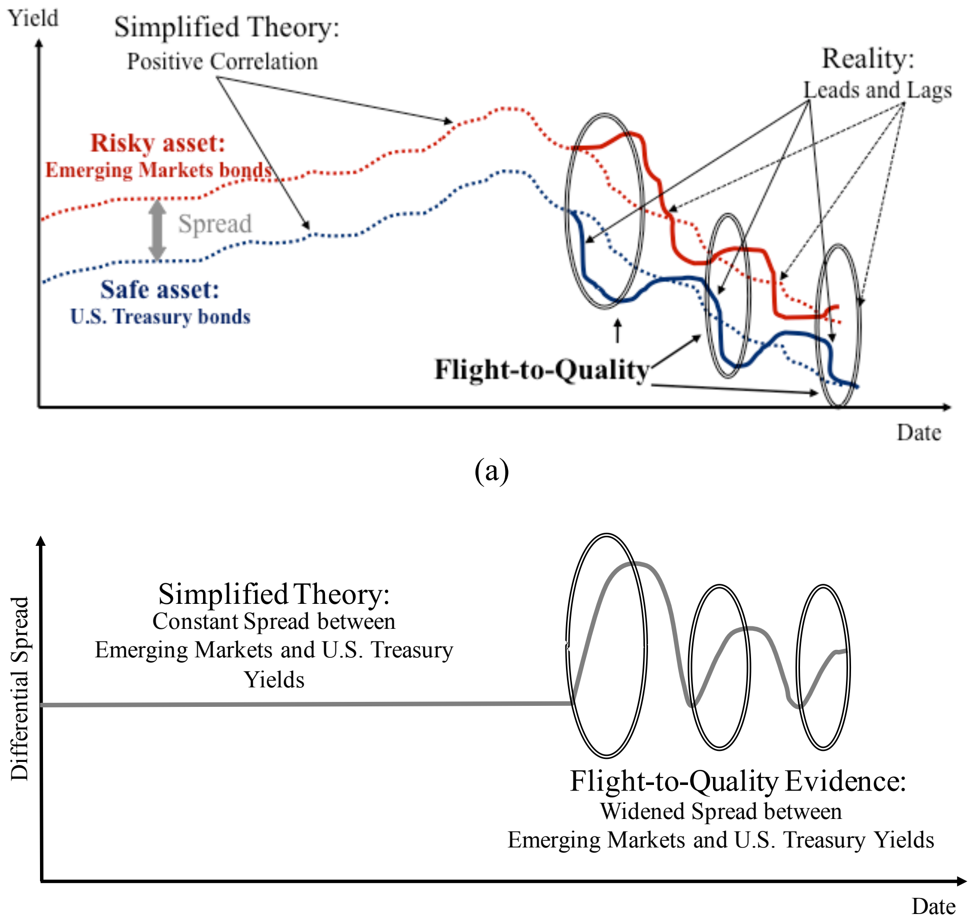
The *JPEMSOSD* represents the spread of *EMBI+* portfolio yield over the theoretical U.S. zero-coupon curve. In case of *EMBI+*, the country selection process is based on the country sovereign credit rating level, while *EMBI Global* (applied for the Flight-to-Quality total return-based identification methodology) selection process allows for the broader array of counties and relies on the World Bank income levels classification. Thus, according to the described above, is considered that *JPEMSOSD* index represents a suitable alternative measure to be used in studies of Flight-to-Quality events, for instance, for preliminary analysis of those episodes´ length.

#### 3.1.2.2. Analysis of Flight-to-Quality time windows

In order to explain the concept of the spread-based approach, applicable to the analysis of time intervals of Flights-to-Quality in general, and out of *EM* towards *UST* bonds in particular, it is worth considering the influence, which is exercised by the *UST* interest rates over the *EM* rates. In accordance with Kamin and Kleist (1999) and Arora and Cerisola (2002) among others, an increase in the *UST* interest rates leads to the growth in *EM* yields. The logic of this relationship is the following. The growth in the U.S. interest rate has a negative impact on the ability of debt issuing emerging countries to repay their loans, increasing the likelihood of their default and raising the corresponding risk premium incorporated into bond spread. A rise in the U.S. interest rates could also reduce investors' risk appetite, reducing their exposure to risky markets and, as a result, the availability of financial resources to borrowing countries.

Conversely, a decrease in the U.S. interest rates facilitates debt service payments, reducing the likelihood of default and, as a result, lowering emerging market yields. Another reason for a positive correlation between a decrease in *UST* and in *EM* yields is that investors, seeking to enhance the overall return on their portfolios, switch to *EM* debt whenever yields in mature markets fall.

Consequently, based on the described above theoretical logic, financial market practitioners frequently assume a positive correlation between safe haven *UST* and risky *EM* bonds yields. Graphically, this positive correlation could be illustrated as a constant spread between risk-free and risky debt yields as presented in the left hand side of the Figure 3.1.11 (a). Here, a certain incoherence between such simplified investment considerations and more complex reality resulting in Flights-to-Quality could be easily visualized. An allegedly strong positive correlation between the *UST* and the *EM* bonds yields, represented as a constant spread between these yields, collides with reality: this spread changes with time due to the presence of the leads and lags. The name "*lead*" means that the *UST* price, and consequently yield, is considered as a factor which *lead*s the *EM* bond prices and yields which follow their behavior with a lag or, so to say, lag to respond to the lead. These leads and lags are depicted in the right hand side of the Figure 3.1.11 (a). The same consideration could be performed in terms of the differential spread, which is nothing but a difference in the subjacent yields. An allegedly stable relationship between the *UST* and the *EM* yields could be represented by the straight line as depicted in the left hand side of the Figure 3.1.11 (b). Nevertheless, the reality is more complex. For instance, Bustillo and Velloso (2002) empirically show that positive correlation between 10-year UST bond and the *EMBI* yields disappears, becoming negative in periods of financial crises. Authors ascribe this evidence of simultaneous drop in yields of *UST* bonds and an increase in yields of *EM* bonds, to the Flight-to-Quality phenomena. Bunda et al. (2010) also find that the positive correlation between *EM* bond yields and *UST* interest rates may disappear in a time of stress and risk reassessment, so the Flights-to-Quality is usually observed as a common pattern within the crisis situations.




(b)

**Figure 3.1.11**: Stylized graphs explaining Flight-to-Quality phenomena in differential spread terms.

As illustrated in Figure 3.1.11 (a) and Figure 3.1.11 (b) above, the Flights-to-Quality happen when the changes in the yield of safe *UST* bonds are not accompanied by the yield of risky *EM* bonds. These conditions result in a widening of the *EM* yield spread over *UST* bond yield. The consequence is that investors withdraw their funds from risky investments and fly to quality of risk-free assets. This provokes a further increase in a spread of *EM* bond yields over the risk-free interest rate, transforming the initial tendency into a vicious circle as depicted in the Figure 3.1.12 for the Flight-to-Quality of the A-subtype of the 1$^{st}$ type.

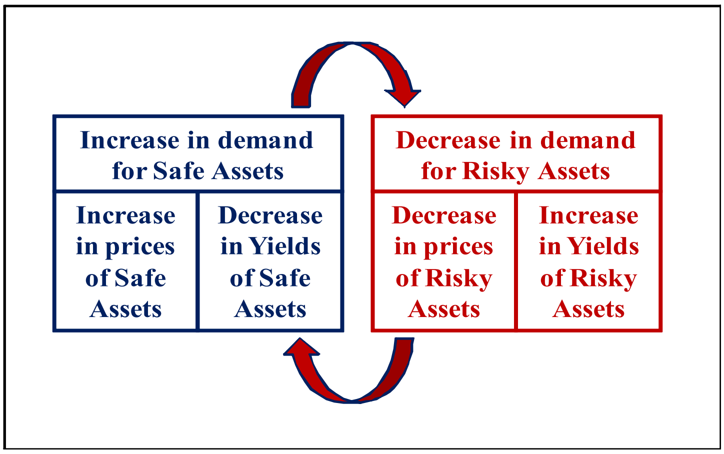



**Figure 3.1.12**: Schematic safe and risky assets relationship under the occurrence of the Flights-to-Quality of the A-subtype of the 1st type.

As it could be inferred from the Figure 3.1.11, the differential spread is a useful parameter to look at while detecting Flights-to-Quality. For example, Barth et al. (2009) apply the *EM* yield spread over *UST* in order to detect the periods of crises happened in developing economies within the period from 1998 to 2009. Authors state that in a time of turmoil, global demand for the *UST* leads to a huge increase in a spread of *EM* securities over the *UST* assets. Other researchers such as, for example, Ross and Bernal (2007) also employ *EM* sovereign bonds spread over *UST* yield with the objective to describe *EM* bond "sell-offs" during the period of 2003-2007, which is but the Flight-to-Quality out of emerging economies.

The spread-based approach is widely used in analyses of crisis situations and Flights-to-Quality not only out of *EM* but also out of other riskier fixed income securities issued in the developed economies. For example, Blinder and Zandi (2010) analyze the non-investment grade "*junk bonds*" spread over the *UST* bonds and state that it widens alarmingly during the crisis, but become narrow under the normal market conditions.

Following the explained above logic, the differential spread index *JPEMSOSD* is employed herein to assess the maximum length of the Flight-to-Quality windows.

Below, to illustrate an application of the differential spread-based approach, the behavior of *JPEMSOSD* index for the period from 01.03.2004 to 30.06.2004 is depicted in the Figure 3.1.13. The oval indicates the Flight-to-Quality like manifestation: within the evidenced time interval the *EM* spread over the *UST* yield widens: hence, one could see an increase in the *JPEMSOSD* values over the period of 13.04.2004 – 10.05.2004.

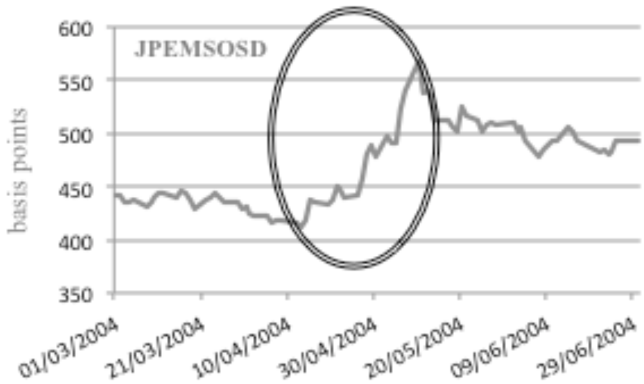
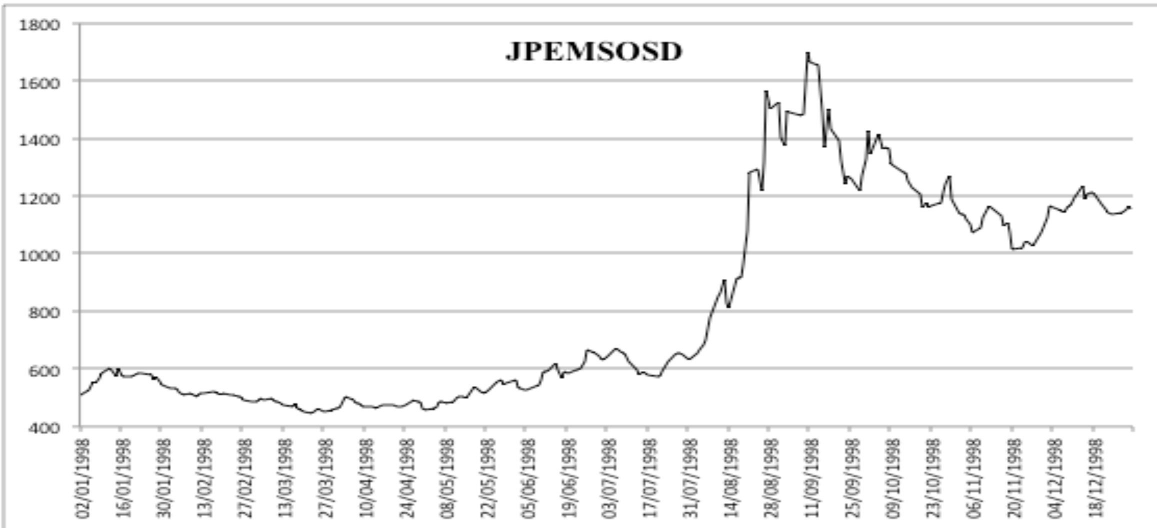
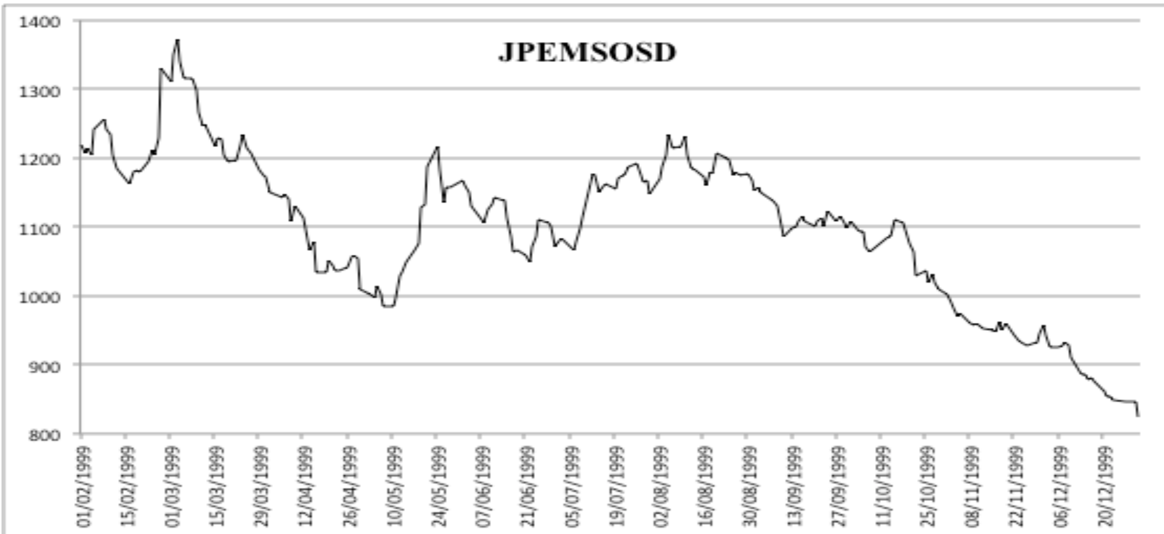


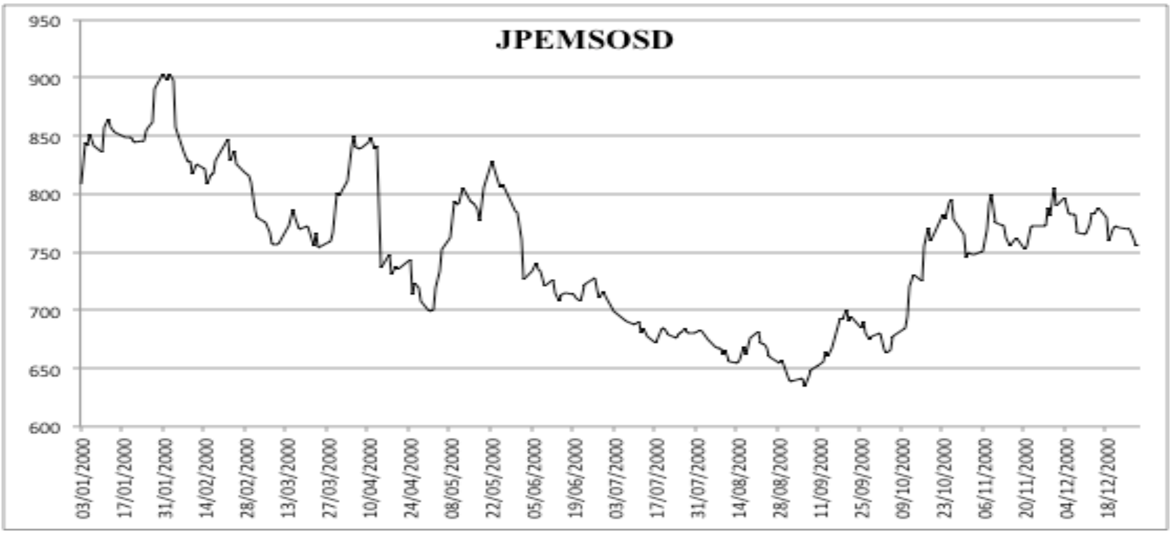

**Figure 3.1.13**: *JPEMSOSD* index behavior exhibiting increase (13.04.2004 – 10.05.2004).

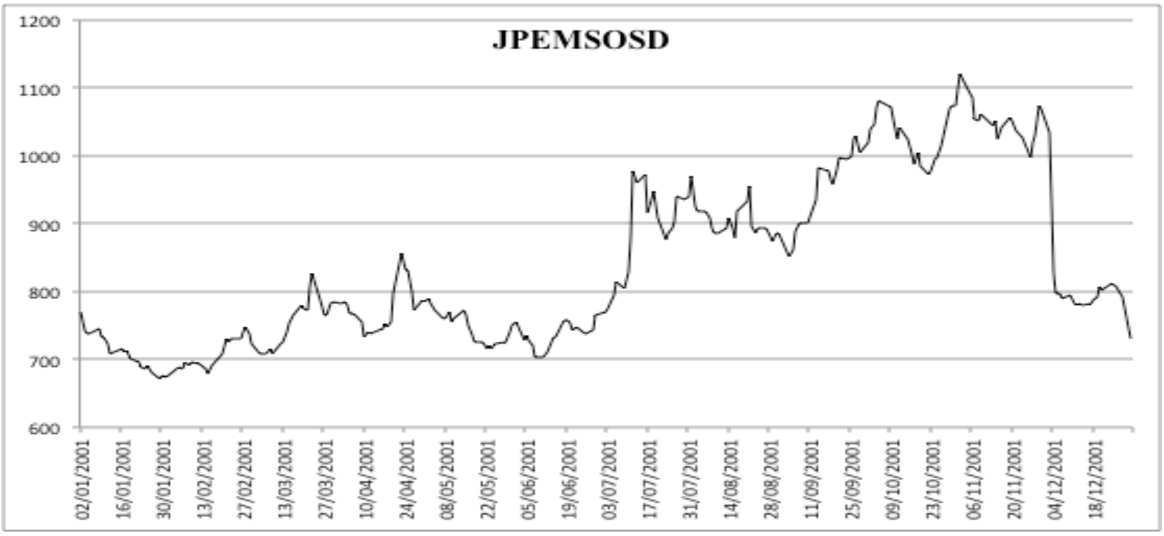
The preliminary visual analyses of the *JPEMSOSD* index behavior indicates that Flight-to-Quality, being sharp increases in *JPEMSOSD* values, are short run events whose duration stays below 1.5 months on a time scale (see Figure 3.1.14 below).

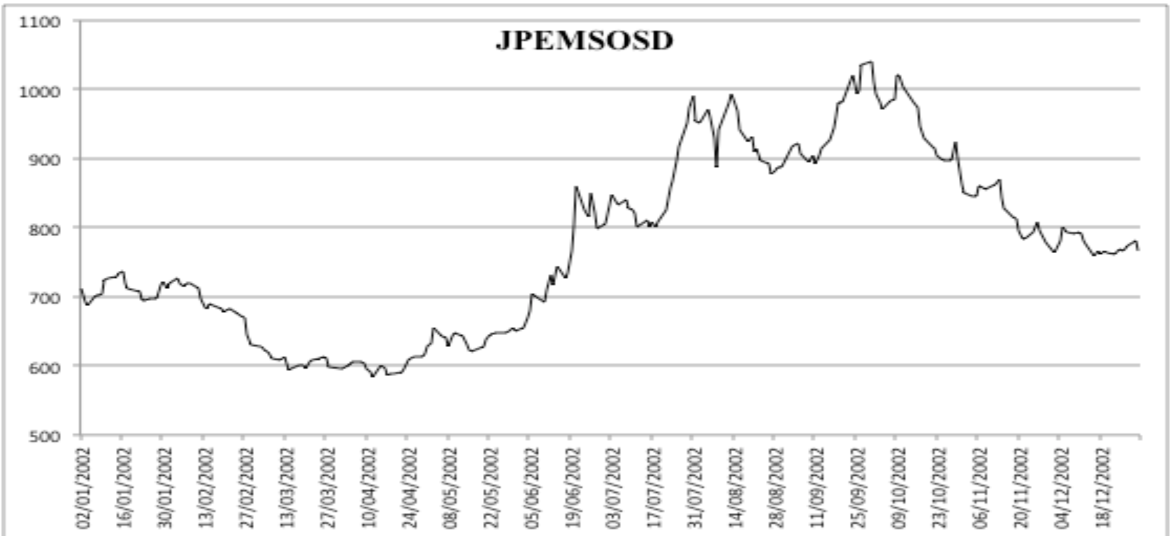
For example, considering the first chart of Figure 3.1.14, which represent the behavior of *JPEMSOSD* over the 1998, can be seen the sharp increase in *JPEMSOSD* value from the 572 basis points to 1697 basis points over the period from the 20.07.1998 to 10.09.1998 respectively. This period covers 38 working days.

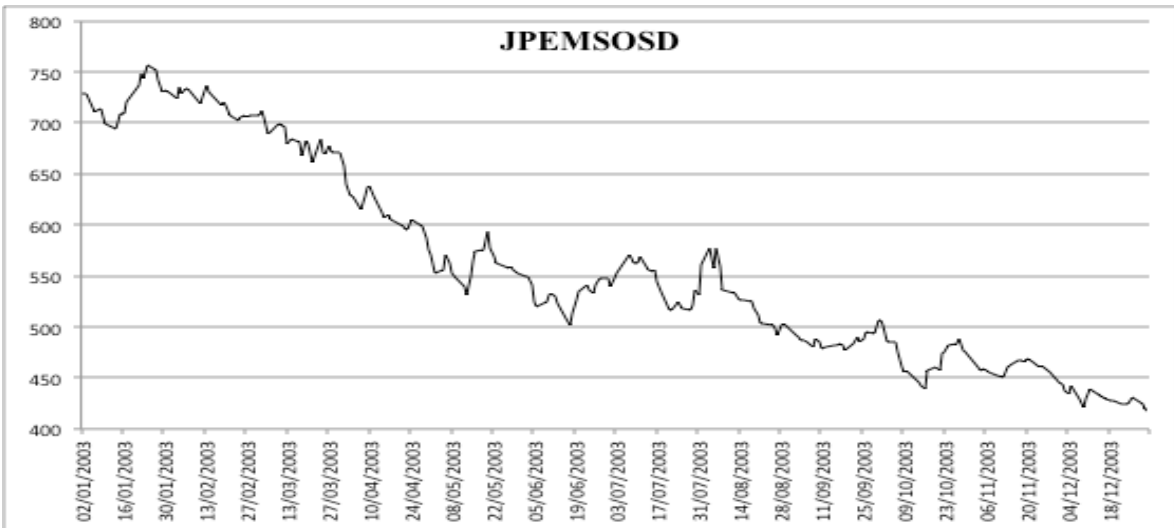

JPEMSOSD
1800
1600
1400
1200
1000
800
600
400
02/01/1998
16/01/1998
30/01/1998
13/02/1998
27/02/1998
13/03/1998
27/03/1998
10/04/1998
24/04/1998
08/05/1998
22/05/1998
05/06/1998
19/06/1998
03/07/1998
17/07/1998
31/07/1998
14/08/1998
28/08/1998
11/09/1998
25/09/1998
09/10/1998
23/10/1998
06/11/1998
20/11/1998
04/12/1998
18/12/1998

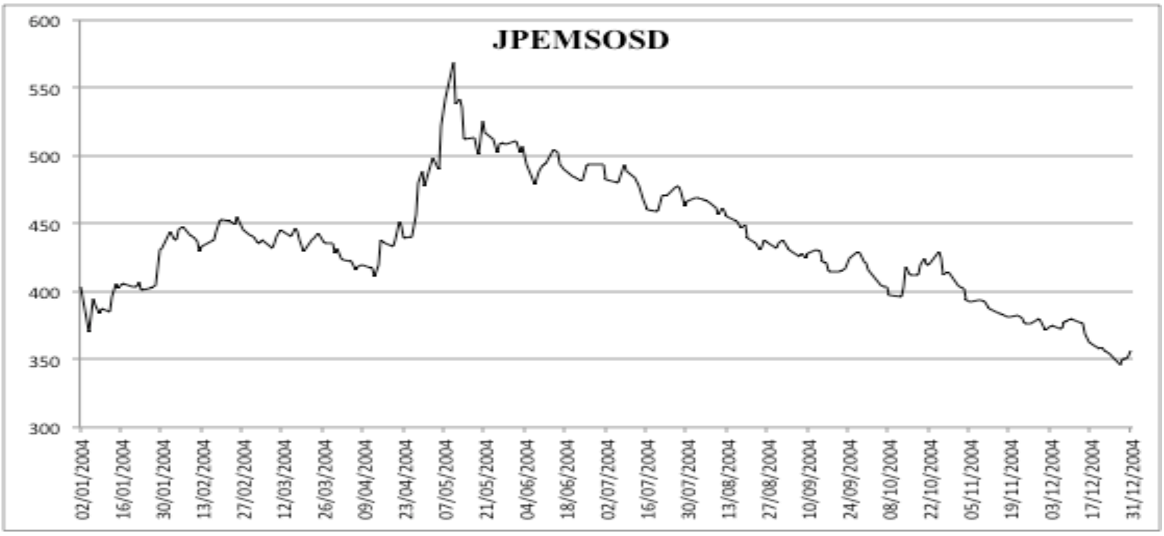

JPEMSOSD
1400
1300
1200
1100
1000
900
800
01/02/1999
15/02/1999
01/03/1999
15/03/1999
29/03/1999
12/04/1999
26/04/1999
10/05/1999
24/05/1999
07/06/1999
21/06/1999
05/07/1999
19/07/1999
02/08/1999
16/08/1999
30/08/1999
13/09/1999
27/09/1999
11/10/1999
25/10/1999
08/11/1999
22/11/1999
06/12/1999
20/12/1999

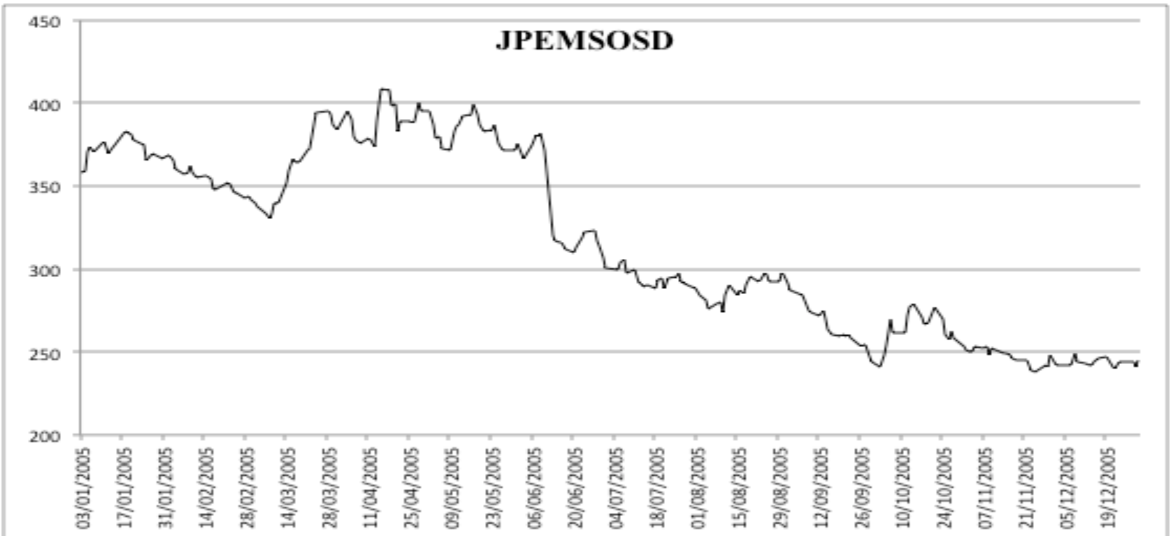

JPEMSOSD
950
900
850
800
750
700
650
600
03/01/2000
17/01/2000
31/01/2000
14/02/2000
28/02/2000
13/03/2000
27/03/2000
10/04/2000
24/04/2000
08/05/2000
22/05/2000
05/06/2000
19/06/2000
03/07/2000
17/07/2000
31/07/2000
14/08/2000
28/08/2000
11/09/2000
25/09/2000
09/10/2000
23/10/2000
06/11/2000
20/11/2000
04/12/2000
18/12/2000

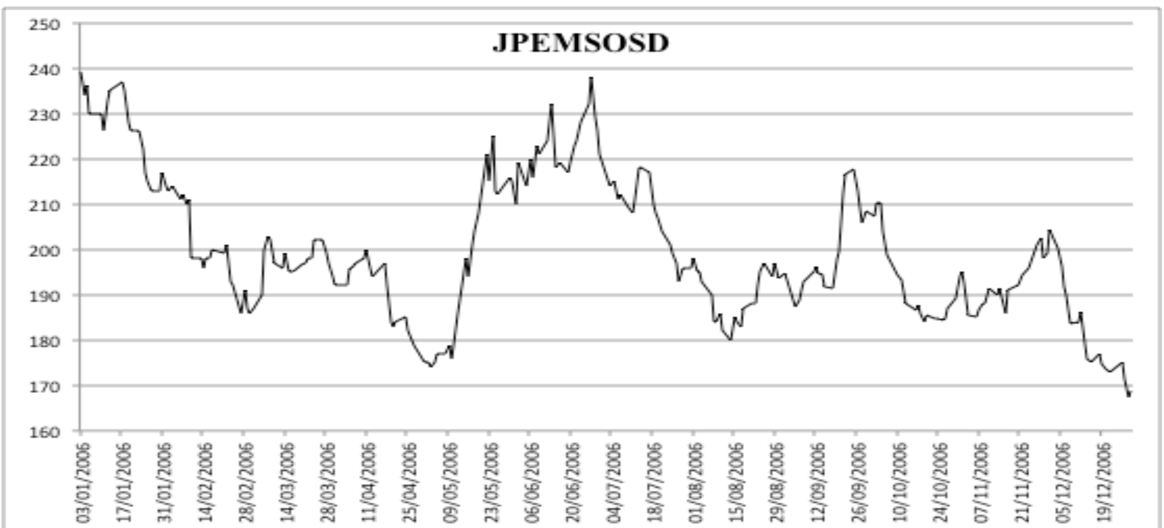

JPEMSOSD

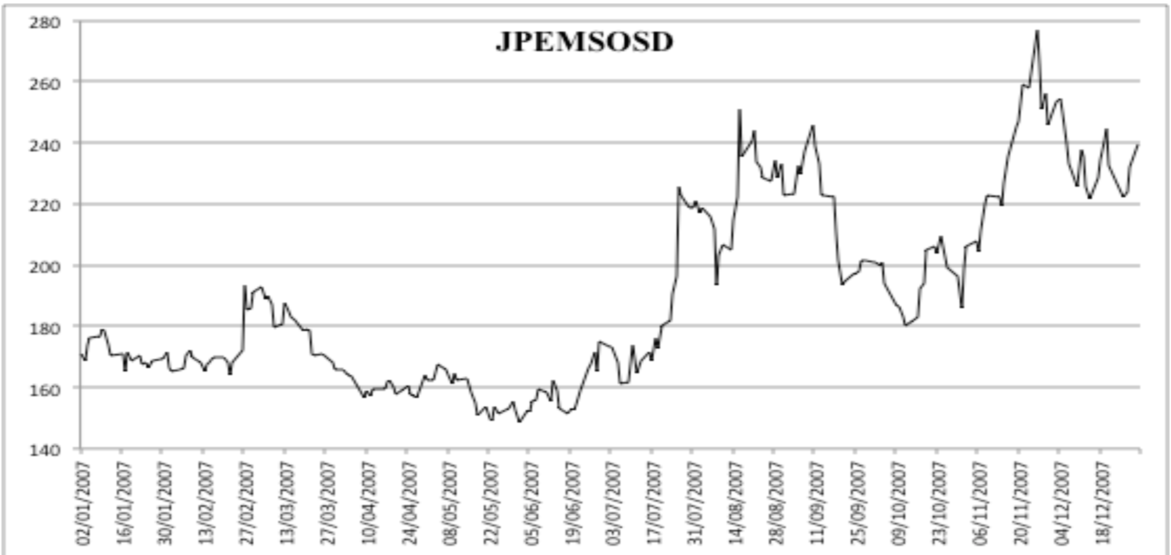

JPEMSOSD

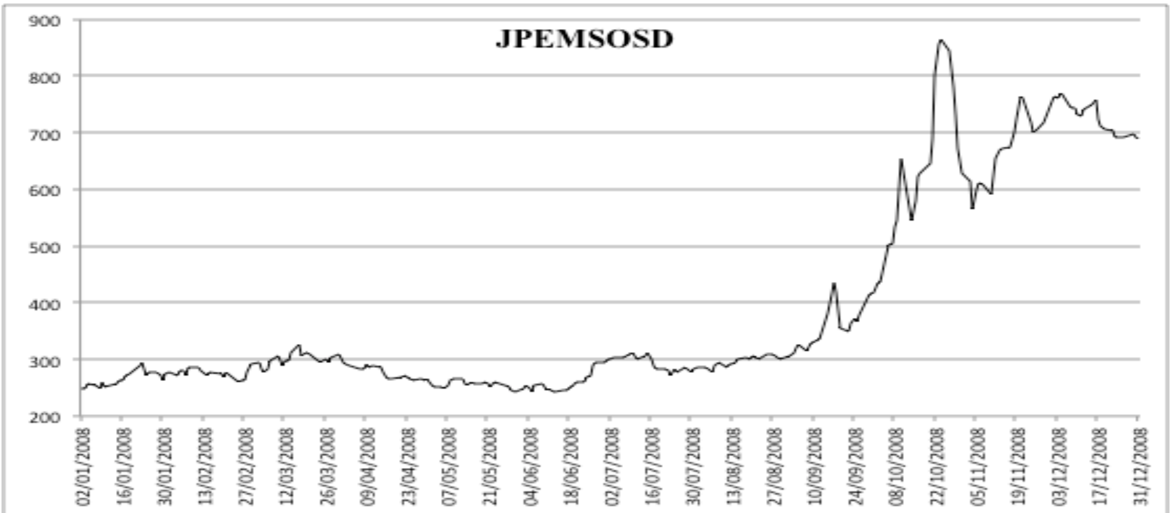

JPEMSOSD

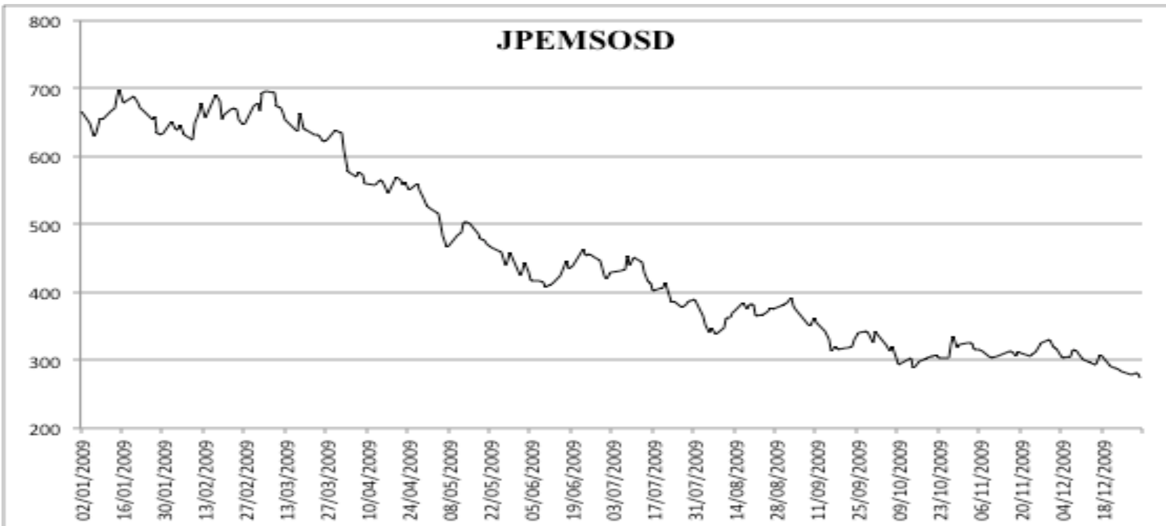

JPEMSOSD
600
550
500
450
400
350
300
02/01/2004
16/01/2004
30/01/2004
13/02/2004
27/02/2004
12/03/2004
26/03/2004
09/04/2004
23/04/2004
07/05/2004
21/05/2004
04/06/2004
18/06/2004
02/07/2004
16/07/2004
30/07/2004
13/08/2004
27/08/2004
10/09/2004
24/09/2004
08/10/2004
22/10/2004
05/11/2004
19/11/2004
03/12/2004
17/12/2004
31/12/2004


JPEMSOSD
450
400
350
300
250
200
03/01/2005
17/01/2005
31/01/2005
14/02/2005
28/02/2005
14/03/2005
28/03/2005
11/04/2005
25/04/2005
09/05/2005
23/05/2005
06/06/2005
20/06/2005
04/07/2005
18/07/2005
01/08/2005
15/08/2005
29/08/2005
12/09/2005
26/09/2005
10/10/2005
24/10/2005
07/11/2005
21/11/2005
05/12/2005
19/12/2005


JPEMSOSD
250
240
230
220
210
200
190
180
170
160
03/01/2006
17/01/2006
31/01/2006
14/02/2006
28/02/2006
14/03/2006
28/03/2006
11/04/2006
25/04/2006
09/05/2006
23/05/2006
06/06/2006
20/06/2006
04/07/2006
18/07/2006
01/08/2006
15/08/2006
29/08/2006
12/09/2006
26/09/2006
10/10/2006
24/10/2006
07/11/2006
21/11/2006
05/12/2006
19/12/2006


JPEMSOSD
280
260
240
220
200
180
160
140
02/01/2007
16/01/2007
30/01/2007
13/02/2007
27/02/2007
13/03/2007
27/03/2007
10/04/2007
24/04/2007
08/05/2007
22/05/2007
05/06/2007
19/06/2007
03/07/2007
17/07/2007
31/07/2007
14/08/2007
28/08/2007
11/09/2007
25/09/2007
09/10/2007
23/10/2007
06/11/2007
20/11/2007
04/12/2007
18/12/2007


JPEMSOSD
900
800
700
600
500
400
300
200
02/01/2008
16/01/2008
30/01/2008
13/02/2008
27/02/2008
12/03/2008
26/03/2008
09/04/2008
23/04/2008
07/05/2008
21/05/2008
04/06/2008
18/06/2008
02/07/2008
16/07/2008
30/07/2008
13/08/2008
27/08/2008
10/09/2008
24/09/2008
08/10/2008
22/10/2008
05/11/2008
19/11/2008
03/12/2008
17/12/2008
31/12/2008


JPEMSOSD
800
700
600
500
400
300
200
02/01/2009
16/01/2009
30/01/2009
13/02/2009
27/02/2009
13/03/2009
27/03/2009
10/04/2009
24/04/2009
08/05/2009
22/05/2009
05/06/2009
19/06/2009
03/07/2009
17/07/2009
31/07/2009
14/08/2009
28/08/2009
11/09/2009
25/09/2009
09/10/2009
23/10/2009
06/11/2009
20/11/2009
04/12/2009
18/12/2009

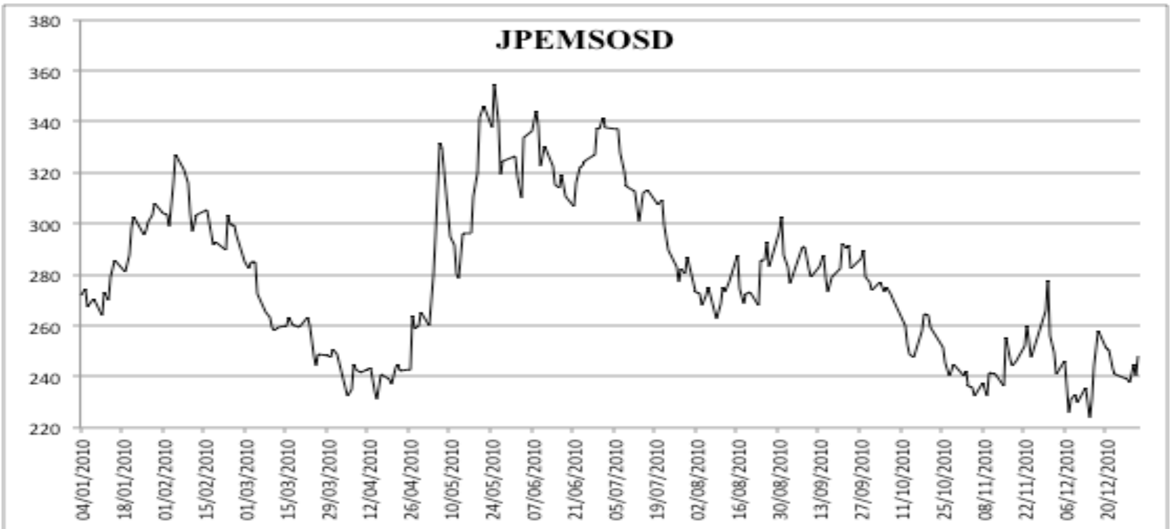



**Figure 3.1.14**: *JPEMSOSD* index behavior within 1998 – 2010 (in basis points).

Even so, to be able to include in the Flight-to-Quality identification approach eventual occurrences with a superior time length, a probe interval equal to two months is chosen. The proposed automated identification mechanism is able to identify Flight-to-Quality with a maximum duration of 45 working days corresponding on average to two calendar months. The application of the total return-based Flight-to-Quality identification algorithm, discussed in the section 3.1.1.3, is applied to the *EM-UST* Flights-to-Quality further on.

**3.1.2.3. Total Return-based Technique: Emerging Markets vs. U.S. Treasury bonds**

In order to identify on *ex-post* basis Flights-to-Quality out of *EM* sovereign debt towards *UST* bonds within the period from January 1998 to December 2010, the proposed herein algebraic algorithm compares the respective total returns of *EMBI* and *ITRROV* bond indexes. It consists of the following three steps derived in section 3.1.1.3.

***1^st^ Step***

For each rolling anchor date *AD* of a chosen 45-day long time interval, 45 different returns (for the trial initial dates varying from 1 to 45 days back into the past) of the *EMBI* index and the respective 45 returns of the *ITRROV* index are calculated within the whole analyzed interval: 1998 - 2010. Thus, the 45 different trial initial dates are employed in the consecutive return calculations using in each turn the same anchor date (*AD*). This means that each time after the anchor date (*AD*) is fixed, the algorithm goes by *1*-day steps into the past until the 45 working day limit and calculates the percentage returns of *EMBI* and *ITRROV* for each of 45 subjacent intervals. Hence, for the considered asset indexes and the chosen anchor date (*AD*), the total return over the *k* days precedent to the anchor date (*AD*) can be described by the following expressions:

$$R_{(AD-k;AD)}^{EMBI} = \frac{EMBI_{(AD)}}{EMBI_{(AD-k)}} - 1\,; \tag{3.1.6}$$

$$R_{(AD-k;AD)}^{ITRROV} = \frac{ITRROV_{(AD)}}{ITRROV_{(AD-k)}} - 1\,, \tag{3.1.7}$$

where $R^{EMBI}$ and $R^{ITRROV}$ are the returns of the respective *EMBI* and *ITRROV* indexes;

*AD* is an anchor date consecutively assuming all the dates within the analyzed historical period, hence $AD \in [01.01.1998, 31.12.2010]$;

*k* is a number of days within which the returns of *EMBI* and *ITRROV* are calculated: $k \in [1,45]$.

***2**^{nd}* ***Step***

The 45 differences of *ITRROV* and *EMBI* returns ($\Delta R_k$) are calculated by the following formula:

$$\Delta R_{k(AD)} = R^{ITRROV}_{(AD-k,\,AD)} - R^{EMBI}_{(AD-k,AD)}, \tag{3.1.8}$$

where $k \in [1,45]$.

As it could be seen in Table 3.1.2, for example, for the anchor date (*AD*) 16.01.1998 the 5-day returns of the *ITRROV* and *EMBI* indices are, respectively, -0.52% and 0.68%, the 6-day total returns are -0.06% e -0.04%, and the 7-day total returns are 0.32% and -0.63%, respectively. Consequently, the difference in 5-day total returns of the *ITRROV* and *EMBI* equals to -1.20%, the 6-day difference equals to -0.02%, and the 7-day total returns difference is 0.94%.

| ITRROV Index | | JPEGCOMP Index | | | 5 days | | | 6 days | | | 7 days | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Date | Px Last | Date | Px Last | TR ITRROV | TR EMBI | Δ | TR ITRROV | TR EMBI | Δ | TR ITRROV | TR EMBI | Δ |
| 02.01.1998 | 91,18 | 02.01.1998 | 156,70 | | | | | | | | | |
| 05.01.1998 | 91,84 | 05.01.1998 | 156,45 | | | | | | | | | |
| 06.01.1998 | 91,93 | 06.01.1998 | 154,63 | | | | | | | | | |
| 07.01.1998 | 91,69 | 07.01.1998 | 154,69 | | | | | | | | | |
| 08.01.1998 | 92,04 | 08.01.1998 | 153,78 | | | | | | | | | |
| 09.01.1998 | 92,46 | 09.01.1998 | 152,68 | 1,40% | -2,57% | **3,97%** | | | | | | |
| 12.01.1998 | 92,50 | 12.01.1998 | 151,45 | 0,71% | -3,19% | **3,91%** | 1,44% | -3,35% | **4,79%** | | | |
| 13.01.1998 | 92,42 | 13.01.1998 | 153,20 | 0,53% | -0,92% | **1,45%** | 0,62% | -2,07% | **2,69%** | 1,35% | -2,23% | **3,58%** |
| 14.01.1998 | 92,26 | 14.01.1998 | 153,82 | 0,62% | -0,56% | **1,18%** | 0,35% | -0,52% | **0,88%** | 0,45% | -1,68% | **2,13%** |
| 15.01.1998 | 92,23 | 15.01.1998 | 152,18 | 0,21% | -1,04% | **1,25%** | 0,59% | -1,62% | **2,21%** | 0,32% | -1,58% | **1,90%** |
| 16.01.1998 | 91,98 | 16.01.1998 | 153,72 | -0,52% | 0,68% | **-1,20%** | -0,06% | -0,04% | **-0,02%** | 0,32% | -0,63% | **0,94%** |
| 20.01.1998 | 91,89 | 20.01.1998 | 154,02 | -0,66% | 1,70% | **-2,36%** | -0,62% | 0,88% | **-1,50%** | -0,16% | 0,16% | **-0,32%** |
| 21.01.1998 | 92,01 | 21.01.1998 | 152,86 | -0,44% | -0,22% | **-0,21%** | -0,52% | 0,93% | **-1,46%** | -0,49% | 0,12% | **-0,61%** |
| 22.01.1998 | 91,93 | 22.01.1998 | 153,00 | -0,35% | -0,53% | **0,18%** | -0,52% | -0,13% | **-0,39%** | -0,61% | 1,03% | **-1,63%** |
| 23.01.1998 | 91,36 | 23.01.1998 | 152,36 | -0,94% | 0,12% | **-1,06%** | -0,97% | -0,95% | **-0,03%** | -1,14% | -0,55% | **-0,59%** |
| 26.01.1998 | 91,67 | 26.01.1998 | 153,23 | -0,33% | -0,32% | **-0,01%** | -0,60% | 0,69% | **-1,29%** | -0,63% | -0,38% | **-0,25%** |
| 27.01.1998 | 91,38 | 27.01.1998 | 154,29 | -0,55% | 0,18% | **-0,73%** | -0,65% | 0,37% | **-1,03%** | -0,92% | 1,39% | **-2,31%** |
| 28.01.1998 | 91,43 | 28.01.1998 | 153,94 | -0,63% | 0,71% | **-1,34%** | -0,50% | -0,05% | **-0,44%** | -0,60% | 0,15% | **-0,74%** |
| 29.01.1998 | 91,96 | 29.01.1998 | 155,44 | 0,03% | 1,59% | **-1,56%** | -0,05% | 1,68% | **-1,74%** | 0,08% | 0,92% | **-0,83%** |
| 30.01.1998 | 92,17 | 30.01.1998 | 156,97 | 0,89% | 3,02% | **-2,14%** | 0,26% | 2,59% | **-2,34%** | 0,17% | 2,69% | **-2,52%** |

**Table 3.1.2**: Extract from the spreadsheet used for Total Return calculations of the ITRROV and EMBI indexes over diverse time intervals augmenting from the left to the right horizontally for different anchor dates (AD) growing down the vertical scale.

For each anchor date (*AD*) the maximum value out of the 45 return differences between *ITRROV* and *EMBI* ( $\Delta R_{(AD)}^{MAX\_EMBIvsITRROV}$ ) is to be found. Taking advantage of Table 3.1.2, the search of the maximum delta ( $\Delta R_{(AD)}^{MAX\_EMBIvsITRROV}$ ) in each table row is performed in accordance with the following expression:

$$\Delta R_{(AD)}^{MAX\_EMBIvsITRROV} = \underset{k=1,2,...,45}{MAX}(\Delta R_{k(AD)}) . \qquad (3.1.9)$$

In parallel, the number of days (*k*), which corresponds to the found $\Delta R_{(AD)}^{MAX\_EMBIvsITRROV}$ , is stored as a parameter $N_{AD}$. Later on, in the next 3rd step, this number ($N_{AD}$) will be used for determining the initial dates of Flight-to-Quality events.

The array composed of the values of $\Delta R_{(AD)}^{MAX\_EMBIvsITRROV}$ is used to build the respective curve of maximum differential *EMBI* versus *ITRROV* returns. Below, in the Figure 3.1.15 the extract of this curve for the year 2000 is presented to serve as an example.

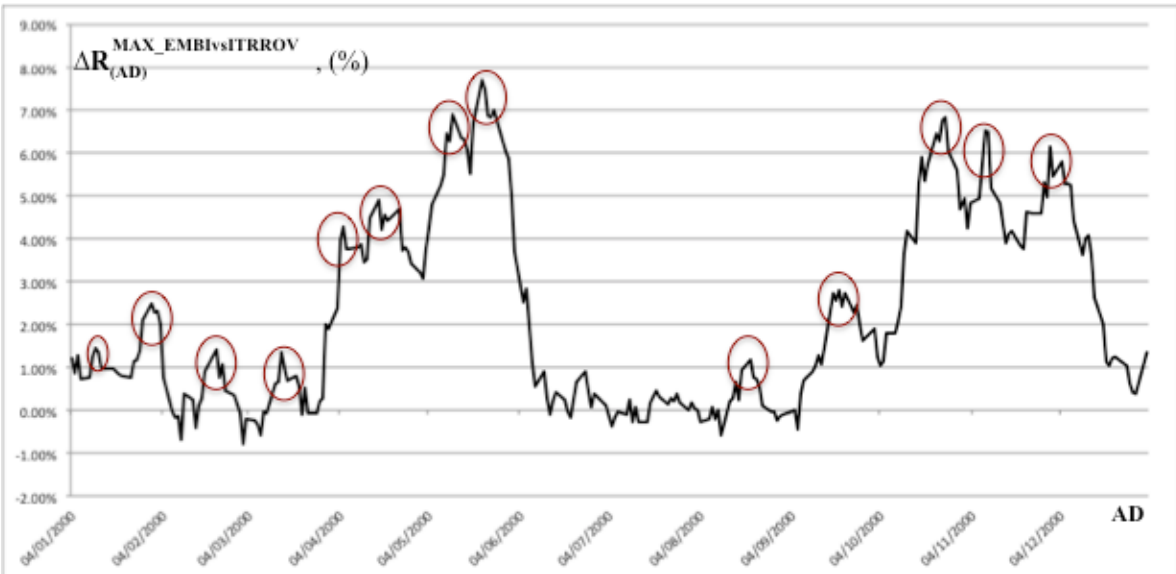



**Figure 3.1.15**: Maximum differences between *ITRROV* and *EMBI* returns in percentage of the initial indexes´ values observed $N_{AD}$ days prior to the anchor date (*AD*) in 2000.
(The local maxima of interest ( >1%) are encircled by ovals.)

The local maxima of the $\Delta R_{(AD)}^{MAX\_EMBIvsITRROV}$, marked by ovals in Figure 3.1.15, correspond to the end dates (*ED*) of the Flight-to-Quality events, as they represent the maximum difference in the returns of the *ITRROV* and *EMBI* observable at $\Delta R_{(AD)}^{MAX\_EMBIvsITRROV}$ curve.

On this step of the Flight-to-Quality identification algorithm, three lists of the selected end dates (*ED*) of the phenomena are composed. In order to be included in the considered selection list, the three filter procedures are performed.

Firstly, the end date (*ED*) of a trialed Flight-to-Quality is included in the first sample selection if the following condition is satisfied:

$$\Delta R_{(ED)}^{MAX\_EMBIvsITRROV} \geq 3\% . \tag{3.1.10}$$

The second selection list includes the end dates (*ED*) exhibiting the maximum differences in the *ITRROV* and *EMBI* indexes performances, which obey the condition below:

$$\Delta R_{(ED)}^{MAX\_EMBIvsITRROV} \geq 2\% . \tag{3.1.11}$$

As it follows from this equation, the events from the first selection list are also present among the other weaker occurrences.

The third selection sample is a list of the end dates (*ED*) corresponding to the maximum differences between *ITRROV* and *EMBI* returns, which satisfy the following condition:

$$\Delta R_{(ED)}^{MAX\_EMBIvsITRROV} \geq 1\% . \tag{3.1.12}$$

By analogy, the third selection list also incorporates the second (and the first) list.

Following these conditions, the three samples of identified end dates (*ED*) of trialed Flights-to-Quality are composed depending on the event impact factor.

***3rd Step***

The third step consists of determining the respective initial date (*ID*) of the event, for each already selected end date (*ED*) of Flight-to-Quality. Thus, for each determined end date (*ED*), the number of the subjacent to the event working days ($N_{ED}$), mentioned in the description of the previous 2nd step of the algorithm, is subtracted from the end date (*ED*) of the Flight-to-Quality to determine the initial date (*ID*) of each occurrences:

$$ID = ED - N_{ED} . \tag{3.1.13}$$

It is worth noting that the initial date (*ID*) corresponds to the maximum difference between the *ITRROV* and *EMBI* total returns calculated for each already selected end date (*ED*), which is nothing but the date corresponding to the $\Delta R_{(ID;\, ED)}^{MAX\_EMBIvsITRROV}$ .

*Internal Structure of major Flights-to-Quality:*

Additionally, there are situations when the same initial date (*ID*) corresponds to the different consecutive end dates ($ED_i$) as it is shown by the black arrows in Figure 3.1.16 below. Such aggregated Flight-to-Quality could be decomposed into a set of weaker Flights-to-Quality. Thus, for each identified end date ($ED_i$), with the exception for $ED_1$, an intermediate initial date ($ID_i$) lying between $ED_{i-1}$ and $ED_i$ should be determined. In the considered example, the highest maximum difference in the returns of the *ITRROV* and *EMBI* ($\Delta R_{(ED)}^{MAX\_EMBIvsITRROV}$) within the period from 10.03.2000 to 14.06.2000 is 7.71%, which takes place on 22.05.2000, as it could be seen in Figure 3.1.16 below. The earliest initial date ($ID_1$) of the aggregated Flight-to-Quality, which corresponds to the latest end date ($ED_4$), is 27.03.2000. But the difference in the returns of the *ITRROV* and *EMBI* ($\Delta R_{(ED)}^{MAX\_EMBIvsITRROV}$) within the identified Flight-to-Quality period represents three other local maximums with values inferior to the value of 7.71% on 22.05.2000. They can be observed on 05.04.2000, 17.04.2000, and 12.05.2000.

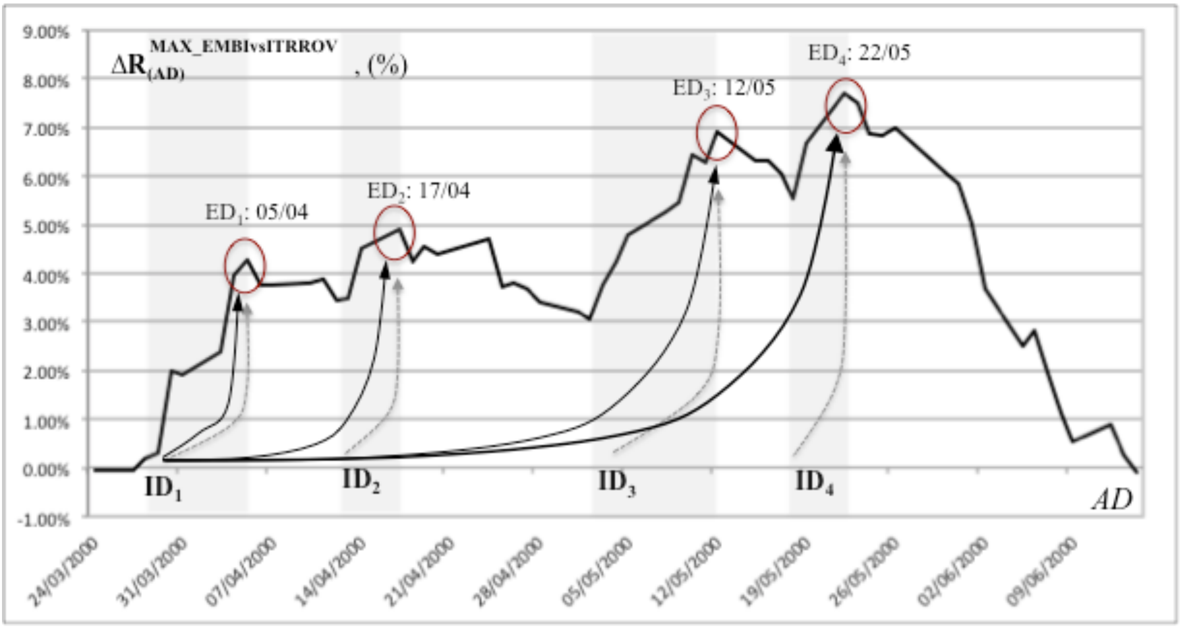



**Figure 3.1.16**: Augmented fragment of Figure 3.1.15 illustrating a possible decomposition of the aggregated Flight-to-Quality (27.03.2000 – 22.05.2000) into the series of four weaker Flights-to-Quality, indicated by dashed arrows.

Consequently, the identified aggregated Flight-to-Quality can be alternatively analyzed as if it was composed of four weaker Flights-to-Quality as it is represented in Table 3.1.3.

| ID | ED | Δ | Aggregated |
|---|---|---|---|
| 27/03/2000 | 05/04/2000 | 4.27% | ^ |
| 12/04/2000 | 17/04/2000 | 1.48% | ^ |
| 02/05/2000 | 12/05/2000 | 3.97% | ^ |
| 18/05/2000 | 22/05/2000 | 2.28% | **7.71%** |

**Table: 3.1.3**: Decomposed Flight-to-Quality (27.03.2000 – 22.05.2000).

In Table 3.1.3. Δ stands for a strength of Flight-to-Quality being the difference between *ITRROV* and *EMBI* returns in percentage in respect to the initial date ($ID_i$) indexes´ values. The shadowed cells represent the earliest initial date ($ID_1$) and the latest end date ($ED_4$) corresponding to the highest maximum difference in the returns of the *ITRROV* and *EMBI* ($\Delta R_{(ED)}^{MAX\_EMBIvsITRROV}$). It is worth commenting that the strength of the aggregated Flight-to-Quality is less than the sum of the weaker Flights-to-Quality into which it could be decomposed. While considered as a sum of the weaker Flights-to-Quality, the augmenting of their aggregated strength is due to the fact that only the time intervals of *EMBI* underperformance are retained, while the periods of its partial recovery are left aside. There are three such periods in the considered example: 05.04.2000 – 12.04.2000; 17.04.2000 – 02.05.2000; and 12.05.2000 – 18.05.2000 which separate the four weaker Flights-to-Quality inside the aggregated major event. Figure 3.1.17 and Figure 3.1.18 below illustrate this decomposition procedure.

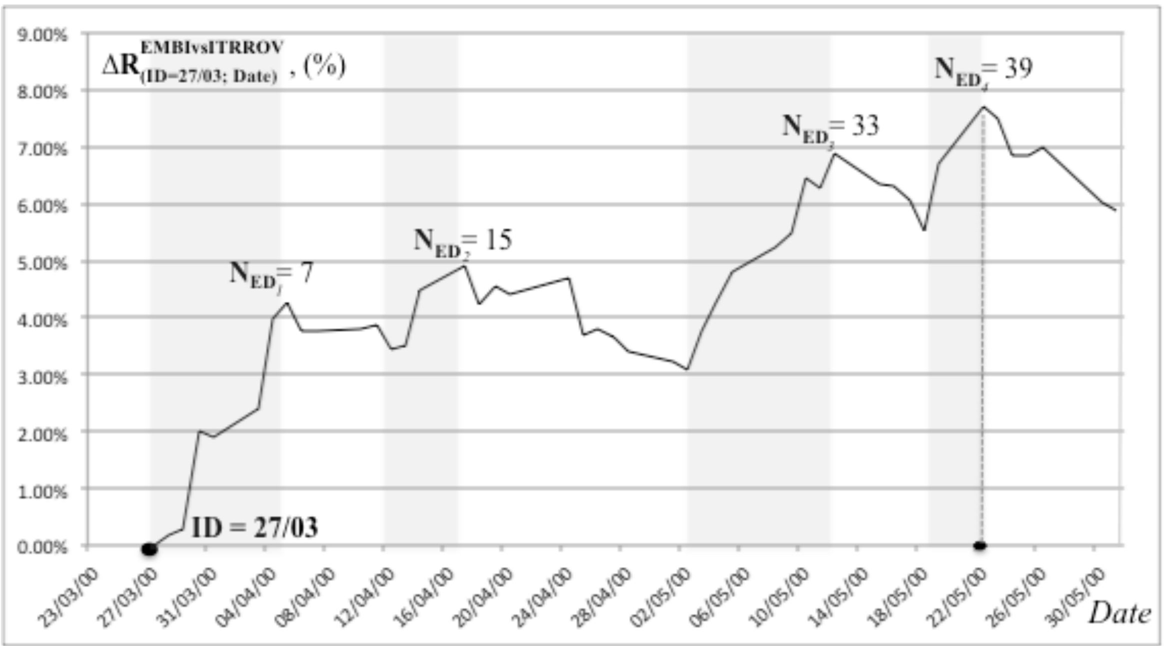



**Figure 3.1.17**: Dynamics of the difference between ITRROV and EMBI returns (in percentage of the earliest ID indexes´ values) within the aggregated Flight-to-Quality (27.03.2000 – 22.05.2000).

Figure 3.1.17 above depicts evolution of the difference between returns of *ITRROV* and *EMBI* in respect to the initial date (*ID*) 27.03.2000, with shadowed intervals corresponding to each of four identified end dates ($ED_i$), where *i* varies from 1 to 4.

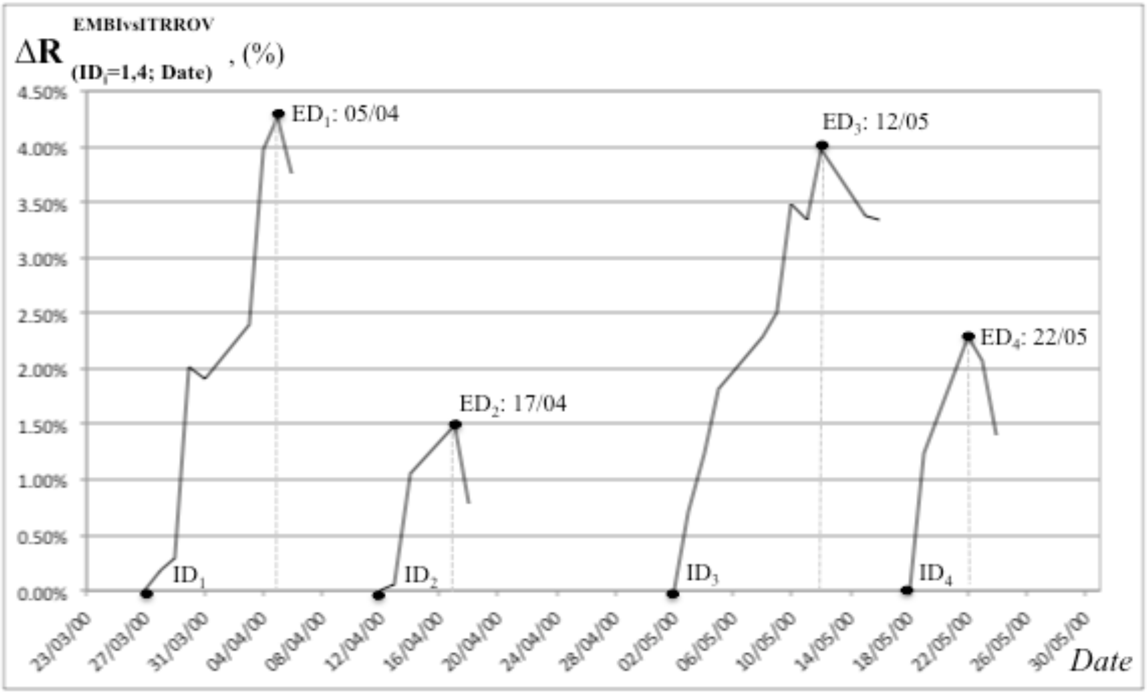



**Figure 3.1.18**: The difference between ITRROV and EMBI returns (in percentage of $ID_i$ indexes´ values for the set of intermediate initial dates $ID_i$) within the aggregated Flight-to-Quality (27.03.2000 – 22.05.2000).

Figure 3.1.18 above describes the aggregated Flight-to-Quality (27.03.2000 – 22.05.2000) as if composed of the four weaker events whose intermediate initial dates ($ID_i$) are 27.03.2000, 12.04.2000, 02.05.2000, and 18.05.2000.

***Results of the Flight-to-Quality Identification Algorithm***

The application of the described 3 steps of the proposed algorithm results in an identification of the initial and the end dates of the 133 Flight-to-Quality manifestations with the difference in the *ITRROV* and *EMBI* indexes performance superior to 1%, 74 Flights-to-Quality with the difference in the *ITRROV* and *EMBI* total returns over 2%, and

50 phenomena with the difference in the *ITRROV* and *EMBI* total returns higher than 3%. The results are represented on annually basis in Tables 3.1.4 – 3.1.16, where shadowing indicates the initial (*ID*) and final (*ED*) dates of the wrapping aggregated Flights-to-Quality, as well as their aggregate strengths and the sets of minor events identified within the wrapping time intervals.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 23/03/1998 | 03/04/1998 | 0.75% | -2.04% | | | 2.79% | 2.79% |
| 2 | 14/04/1998 | 27/04/1998 | -0.66% | -1.80% | | | | 1.14% |
| 3 | 01/05/1998 | 18/05/1998 | 0.29% | -3.48% | ^ | 3.77% | 3.77% | 3.77% |
| 4 | 21/05/1998 | 27/05/1998 | 0.59% | -1.75% | ^ | | 2.34% | 2.34% |
| 5 | 05/06/1998 | 15/06/1998 | 1.14% | -3.14% | ^ | 4.28% | 4.28% | 4.28% |
| 6 | 17/06/1998 | 26/06/1998 | 0.64% | -3.91% | ^ | 4.55% | 4.55% | 4.55% |
| 7 | 01/07/1998 | 06/07/1998 | 0.33% | -1.61% | **9.40%** | | | 1.94% |
| 8 | 20/07/1998 | 27/07/1998 | 0.15% | -3.40% | ^ | 3.55% | 3.55% | 3.55% |
| 9 | 31/07/1998 | 12/08/1998 | 0.85% | -10.89% | ^ | 11.74% | 11.74% | 11.74% |
| 10 | 14/08/1998 | 27/08/1998 | 1.33% | -22.92% | ^ | 24.25% | 24.25% | 24.25% |
| 11 | 02/09/1998 | 10/09/1998 | 1.62% | -8.24% | **36.45%** | 9.86% | 9.86% | 9.86% |
| 12 | 28/09/1998 | 05/10/1998 | 2.42% | -4.20% | | 6.62% | 6.62% | 6.62% |
| 13 | 22/10/1998 | 29/10/1998 | 0.74% | -2.70% | | 3.44% | 3.44% | 3.44% |
| 14 | 06/11/1998 | 12/11/1998 | 0.94% | -2.38% | | 3.32% | 3.32% | 3.32% |
| 15 | 23/11/1998 | 14/12/1998 | 1.51% | -6.37% | | 7.88% | 7.88% | 7.88% |

**Table 3.1.4**: Identified Flight-to-Quality events and their impacts in 1998.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 06/01/1999 | 14/01/1999 | 0.42% | -12.18% | | 12.60% | 12.60% | 12.60% |
| 2 | 20/01/1999 | 25/01/1999 | 0.56% | -4.48% | | 5.04% | 5.04% | 5.04% |
| 3 | 04/02/1999 | 08/02/1999 | -0.08% | -1.58% | | | | 1.50% |
| 4 | 16/02/1999 | 03/03/1999 | -1.26% | -3.97% | | | 2.71% | 2.71% |
| 5 | 07/05/1999 | 24/05/1999 | 0.22% | -7.46% | | 7.68% | 7.68% | 7.68% |
| 6 | 22/06/1999 | 28/06/1999 | 0.00% | -1.75% | ^ | | | 1.75% |
| 7 | 06/07/1999 | 12/07/1999 | 0.79% | -2.67% | **4.00%** | 3.46% | 3.46% | 3.46% |
| 8 | 30/07/1999 | 05/08/1999 | 0.27% | -2.05% | | | 2.32% | 2.32% |
| 9 | 17/08/1999 | 20/08/1999 | 0.09% | -1.18% | | | | 1.27% |
| 10 | 10/09/1999 | 24/09/1999 | 0.89% | -0.38% | | | | 1.27% |
| 11 | 08/10/1999 | 15/10/1999 | -0.13% | -1.39% | | | | 1.26% |
| 12 | 26/11/1999 | 01/12/1999 | -0.30% | -1.35% | | | | 1.05% |

**Table 3.1.5**: Identified Flight-to-Quality events and their impacts in 1999.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 03/01/2000 | 12/01/2000 | -0.18% | -1.63% | ^ | | | 1.45% |
| 2 | 24/01/2000 | 31/01/2000 | 0.36% | -1.34% | **2.47%** | | | 1.70% |
| 3 | 15/02/2000 | 22/02/2000 | 1.02% | -0.40% | | | | 1.42% |
| 4 | 10/03/2000 | 15/03/2000 | 0.65% | -0.70% | | | | 1.35% |
| 5 | 27/03/2000 | 05/04/2000 | 1.57% | -2.70% | ^ | 4.27% | 4.27% | 4.27% |
| 6 | 12/04/2000 | 17/04/2000 | -0.12% | -1.60% | ^ | | | 1.48% |
| 7 | 02/05/2000 | 12/05/2000 | -0.91% | -4.88% | ^ | 3.97% | 3.97% | 3.97% |
| 8 | 18/05/2000 | 22/05/2000 | 0.62% | -1.66% | **7.71%** | | 2.28% | 2.28% |
| 9 | 11/08/2000 | 21/08/2000 | 0.19% | -0.99% | | | | 1.18% |
| 10 | 06/09/2000 | 18/09/2000 | -0.55% | -3.27% | ^ | | 2.72% | 2.72% |
| 11 | 04/10/2000 | 26/10/2000 | 1.55% | -4.31% | **6.82%** | 5.86% | 5.86% | 5.86% |
| 12 | 02/11/2000 | 08/11/2000 | -0.42% | -2.79% | | | 2.37% | 2.37% |
| 13 | 21/11/2000 | 30/11/2000 | 1.18% | -1.17% | | | 2.35% | 2.35% |

**Table 3.1.6**: Identified Flight-to-Quality events and their impacts in 2000.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 29/01/2001 | 07/02/2001 | 0.91% | -0.24% | | | | 1.15% |
| 2 | 15/02/2001 | 28/02/2001 | 1.62% | -1.56% | ^ | 3.18% | 3.18% | 3.18% |
| 3 | 09/03/2001 | 23/03/2001 | 0.87% | -4.33% | ^ | 5.20% | 5.20% | 5.20% |
| 4 | 28/03/2001 | 03/04/2001 | 0.33% | -1.02% | ^ | | | 1.35% |
| 5 | 10/04/2001 | 23/04/2001 | -0.20% | -5.79% | **7.60%** | 5.59% | 5.59% | 5.59% |
| 6 | 24/05/2001 | 01/06/2001 | 0.86% | -0.74% | | | | 1.60% |
| 7 | 08/06/2001 | 18/06/2001 | 0.76% | -1.85% | ^ | | 2.61% | 2.61% |
| 8 | 26/06/2001 | 12/07/2001 | 0.09% | -9.78% | **11.32%** | 9.87% | 9.87% | 9.87% |
| 9 | 23/07/2001 | 01/08/2001 | 0.42% | -3.23% | | 3.65% | 3.65% | 3.65% |
| 10 | 09/08/2001 | 14/08/2001 | 0.30% | -0.71% | | | | 1.01% |
| 11 | 16/08/2001 | 21/08/2001 | 0.29% | -3.11% | | 3.40% | 3.40% | 3.40% |
| 12 | 04/09/2001 | 14/09/2001 | 2.37% | -3.92% | ^ | 6.29% | 6.29% | 6.29% |
| 13 | 19/09/2001 | 05/10/2001 | 1.41% | -3.35% | ^ | 4.76% | 4.76% | 4.76% |
| 14 | 22/10/2001 | 02/11/2001 | 1.68% | -4.53% | **10.72%** | 6.21% | 6.21% | 6.21% |
| 15 | 15/11/2001 | 19/11/2001 | 0.03% | -1.25% | | | | 1.28% |
| 16 | 26/11/2001 | 30/11/2001 | 1.15% | -2.26% | | 3.41% | 3.41% | 3.41% |
| 17 | 14/12/2001 | 24/12/2001 | 0.44% | -1.01% | | | | 1.45% |

**Table 3.1.7**: Identified Flight-to-Quality events and their impacts in 2001.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 04/01/2002 | 15/01/2002 | 1.96% | -0.32% | | | 2.28% | 2.28% |
| 2 | 24/01/2002 | 04/02/2002 | 0.95% | -0.71% | | | | 1.66% |
| 3 | 12/04/2002 | 10/05/2002 | 0.89% | -2.16% | | 3.05% | 3.05% | 3.05% |
| 4 | 16/05/2002 | 06/06/2002 | 1.14% | -2.80% | ^ | 3.94% | 3.94% | 3.94% |
| 5 | 10/06/2002 | 21/06/2002 | 1.51% | -4.89% | **10.55%** | 6.40% | 6.40% | 6.40% |
| 6 | 28/06/2002 | 30/07/2002 | 1.68% | -5.34% | | 7.02% | 7.02% | 7.02% |
| 7 | 08/08/2002 | 13/08/2002 | 1.31% | -2.80% | | 4.11% | 4.11% | 4.11% |
| 8 | 30/08/2002 | 23/09/2002 | 2.25% | -2.31% | | 4.56% | 4.56% | 4.56% |
| 9 | 25/09/2002 | 30/09/2002 | 0.81% | -1.06% | | | | 1.87% |
| 10 | 04/10/2002 | 09/10/2002 | 0.54% | -1.34% | | | | 1.88% |
| 11 | 02/12/2002 | 05/12/2002 | 0.57% | -0.86% | | | | 1.43% |
| 12 | 23/12/2002 | 30/12/2002 | 1.06% | 0.04% | | | | 1.02% |

**Table 3.1.8**: Identified Flight-to-Quality events and their impacts in 2002.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 13/01/2003 | 24/01/2003 | 1.25% | -1.26% | | | 2.51% | 2.51% |
| 2 | 13/05/2003 | 20/05/2003 | 1.41% | -1.61% | | 3.02% | 3.02% | 3.02% |
| 3 | 17/06/2003 | 23/06/2003 | -0.22% | -2.21% | ^ | | | 1.99% |
| 4 | 25/06/2003 | 07/07/2003 | -1.38% | -3.07% | **3.13%** | | | 1.69% |
| 5 | 21/07/2003 | 06/08/2003 | -0.74% | -3.73% | | | 2.99% | 2.99% |
| 6 | 19/09/2003 | 30/09/2003 | 1.33% | 0.17% | | | | 1.16% |
| 7 | 16/10/2003 | 28/10/2003 | 1.51% | -0.71% | | | 2.22% | 2.22% |

**Table 3.1.9**: Identified Flight-to-Quality events and their impacts in 2003.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 08/01/2004 | 06/02/2004 | 1.05% | -1.96% | | 3.01% | 3.01% | 3.01% |
| 2 | 12/02/2004 | 19/02/2004 | 0.24% | -0.87% | | | | 1.11% |
| 3 | 13/04/2004 | 21/04/2004 | -0.53% | -2.35% | ^ | | | 1.82% |
| 4 | 23/04/2004 | 10/05/2004 | -1.37% | -7.92% | **7.59%** | 6.55% | 6.55% | 6.55% |
| 5 | 07/06/2004 | 14/06/2004 | -0.57% | -1.72% | | | | 1.15% |
| 6 | 12/10/2004 | 25/10/2004 | 0.75% | -0.78% | | | | 1.53% |

**Table 3.1.10**: Identified Flight-to-Quality events and their impacts in 2004.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 29/12/2004 | 18/01/2005 | 0.81% | -0.57% | | | | 1.38% |
| 2 | 08/03/2005 | 15/04/2005 | 0.87% | -3.23% | | 4.10% | 4.10% | 4.10% |
| 3 | 03/10/2005 | 14/10/2005 | -0.34% | -2.85% | | | 2.51% | 2.51% |

**Table 3.1.11**: Identified Flight-to-Quality events and their impacts in 2005.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 27/02/2006 | 10/04/2006 | -1.14% | -2.94% | | | | 1.80% |
| 2 | 03/05/2006 | 24/05/2006 | 0.73% | -2.22% | ^ | | 2.95% | 2.95% |
| 3 | 01/06/2006 | 13/06/2006 | 0.85% | -0.20% | ^ | | | 1.05% |
| 4 | 16/06/2006 | 27/06/2006 | -0.24% | -1.71% | **3.65%** | | | 1.47% |
| 5 | 05/09/2006 | 22/09/2006 | 1.11% | -0.24% | | | | 1.35% |

**Table 3.1.12**: Identified Flight-to-Quality events and their impacts in 2006.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 22/02/2007 | 05/03/2007 | 1.21% | -0.18% | | | | 1.39% |
| 2 | 23/05/2007 | 13/06/2007 | -1.17% | -2.70% | ^ | | | 1.53% |
| 3 | 18/06/2007 | 29/06/2007 | 0.77% | -0.49% | ^ | | | 1.26% |
| 4 | 06/07/2007 | 26/07/2007 | 2.25% | -1.57% | **5.08%** | 3.82% | 3.82% | 3.82% |
| 5 | 08/08/2007 | 16/08/2007 | 1.47% | -2.26% | | 3.73% | 3.73% | 3.73% |
| 6 | 04/09/2007 | 10/09/2007 | 1.31% | 0.23% | | | | 1.08% |
| 7 | 15/10/2007 | 24/10/2007 | 1.87% | 0.59% | | | | 1.28% |
| 8 | 31/10/2007 | 12/11/2007 | 1.50% | -0.75% | ^ | | 2.25% | 2.25% |
| 9 | 14/11/2007 | 26/11/2007 | 2.29% | -0.78% | **4.97%** | 3.07% | 3.07% | 3.07% |
| 10 | 14/12/2007 | 20/12/2007 | 1.20% | 0.18% | | | | 1.02% |

**Table 3.1.13**: Identified Flight-to-Quality events and their impacts in 2007.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 26/12/2007 | 04/01/2008 | 2.35% | 0.48% | ^ | | | 1.87% |
| 2 | 10/01/2008 | 23/01/2008 | 2.48% | 0.02% | ^ | | 2.46% | 2.46% |
| 3 | 30/01/2008 | 11/02/2008 | 0.90% | -0.88% | ^ | | | 1.78% |
| 4 | 26/02/2008 | 03/03/2008 | 1.72% | 0.19% | **4.33%** | | | 1.53% |
| 5 | 05/03/2008 | 17/03/2008 | 2.04% | -0.70% | | | 2.74% | 2.74% |
| 6 | 13/06/2008 | 15/07/2008 | 2.73% | -1.21% | | 3.94% | 3.94% | 3.94% |
| 7 | 23/07/2008 | 18/08/2008 | 2.15% | 0.85% | | | | 1.30% |
| 8 | 29/08/2008 | 17/09/2008 | 2.53% | -5.71% | ^ | 8.24% | 8.24% | 8.24% |
| 9 | 22/09/2008 | 10/10/2008 | 0.77% | -16.22% | ^ | 16.99% | 16.99% | 16.99% |
| 10 | 14/10/2008 | 24/10/2008 | 1.43% | -15.82% | **30.53%** | 17.25% | 17.25% | 17.25% |
| 11 | 04/11/2008 | 20/11/2008 | 3.49% | -6.23% | | 9.72% | 9.72% | 9.72% |

**Table 3.1.14**: Identified Flight-to-Quality events and their impacts in 2008.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 06/01/2009 | 15/01/2009 | 1.41% | -1.32% | | | 2.73% | 2.73% |
| 2 | 09/02/2009 | 17/02/2009 | 1.59% | -1.94% | | 3.53% | 3.53% | 3.53% |
| 3 | 26/02/2009 | 06/03/2009 | 0.90% | -1.39% | | | 2.29% | 2.29% |
| 4 | 08/05/2009 | 13/05/2009 | 1.03% | -0.80% | | | | 1.83% |
| 5 | 12/06/2009 | 23/06/2009 | 1.27% | -1.61% | ^ | | 2.88% | 2.88% |
| 6 | 01/07/2009 | 08/07/2009 | 1.27% | -0.38% | **2.96%** | | | 1.65% |
| 7 | 07/08/2009 | 17/08/2009 | 1.75% | -0.45% | ^ | | 2.20% | 2.20% |
| 8 | 21/08/2009 | 02/09/2009 | 1.50% | 0.26% | **2.38%** | | | 1.24% |
| 9 | 16/09/2009 | 28/09/2009 | 0.91% | -0.26% | | | | 1.17% |
| 10 | 14/10/2009 | 28/10/2009 | 0.20% | -2.45% | | | 2.65% | 2.65% |
| 11 | 18/11/2009 | 30/11/2009 | 0.98% | -0.49% | | | | 1.47% |

**Table 3.1.15**: Identified Flight-to-Quality events and their impacts in 2009.

| N | ID | ED | ITRROV | EMBI | Event Impact Parameter | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | Aggregated | over 3% | over 2% | over 1% |
| 1 | 11/01/2010 | 05/02/2010 | 1.65% | -1.57% | | 3.22% | 3.22% | 3.22% |
| 2 | 15/04/2010 | 07/05/2010 | 2.12% | -3.35% | ^ | 5.47% | 5.47% | 5.47% |
| 3 | 13/05/2010 | 25/05/2010 | 1.66% | -2.57% | 6.78% | 4.23% | 4.23% | 4.23% |
| 4 | 03/06/2010 | 08/06/2010 | 0.99% | -0.90% | | | | 1.89% |
| 5 | 21/06/2010 | 29/06/2010 | 1.32% | -0.12% | | | | 1.44% |
| 6 | 09/08/2010 | 16/08/2010 | 1.20% | 0.11% | | | | 1.09% |
| 7 | 23/08/2010 | 31/08/2010 | 0.61% | -1.25% | | | | 1.86% |
| 8 | 14/10/2010 | 19/10/2010 | 0.20% | -0.84% | | | | 1.04% |
| 9 | 05/11/2010 | 16/11/2010 | -1.26% | -3.26% | ^ | | 2.00% | 2.00% |
| 10 | 19/11/2010 | 30/11/2010 | 0.43% | -1.46% | 3.25% | | | 1.89% |
| 11 | 14/12/2010 | 17/12/2010 | 0.53% | -1.13% | | | | 1.66% |

**Table 3.1.16**: Identified Flight-to-Quality events and their impacts in 2010.

Tables 3.1.4 – 3.1.16 above contain the initial (*ID*) and final dates (*ED*) of the Flight-to-Quality occurrences, the performance of *ITRROV* and *EMBI* as well as the differential total return between the *ITRROV* and *EMBI* indexes from the beginning to the end of the subjacent phenomenon compared to the event impact parameter (*EIP*) limit conditions in order to demonstrate that the selection of Flight-to-Quality is dependent on the minimal strength of the events to be selected for specific analyses. The number of identifiable Flights-to-Quality depends on the minimal event impact parameter (*EIP*) that serves as a cut-off criterion being the lower limit to exclude events weaker than this chosen parameter. It could be concluded that the bigger the event impact parameter (*EIP*), the smaller is the number of the Flights-to-Quality to be included in a sample. If the sample of 133 Flights-to-Quality with the event impact parameter (*EIP*) above 1% is considered to be 100%, thus the number of Flights-to-Quality with the event impact parameter (*EIP*) above 2% decreases to 74 representing 56% of the total, and the number of Flights-to-Quality with the event impact parameter (*EIP*) above 3% further drops to 50 representing 38%.

***Empirical Analyses of the Flight-to-Quality Typology***

In order to exemplify the proposed typology of Flight-to-Quality described in the section 3.1.1.2 and explain how Flights-to-Quality impact the comparative behaviors of the total returns of *EMBI* and *ITRROV* indexes during Flights-to-Quality, three Flight-to-Quality examples out of the 133 listed above events, are selected and presented in Figure 3.1.19, Figure 3.1.20, and Figure 3.1.21.

<u>*Example of 1.A–subtype of Flight-to-Quality:*</u>

Figure 3.1.19 below represents the *1.A-subtype* of the 1$^{st}$ type of Flight-to-Quality, characterized by the opposite movements in the total returns of risky *EMBI* and safe *ITRROV* indexes under decreasing mid-term risk-free interest rate, occurred within the period 26.11.2001 – 30.11.2001. The graph on the top of the left hand side in Figure 3.1.19 illustrates the dynamics of the mid-term risk-free interest rate described by the U.S. Generic government 5 year yield (further on referred to by its Bloomberg ticker *USGG5YR*) and the dynamics of the *EMBI*-subjacent interest rate calculated as a sum of *USGG5YR* and converted to percentage points *JPEMSOSD* indexes, measured by the ordinate scale on the right hand side (*rhs*) of the chart. (It is worth mentioning that the *JPEMSOSD* index represents the spread of *EMBI* yield over the theoretical U.S. zero-coupon curve, i.e. the difference in the yields of the *EMBI* and the *UST*.)

The graph on the top of the left hand side in Figure 3.1.19 depicts the decrease in *USGG5YR* by 0.34 p.p. while the *EMBI*-subjacent interest rate increases by 0.38 p.p. within the analyzed period of 26.11.2001 – 30.11.2001. Thus, an increase in risk aversion, and hence in risk premiums, makes *EMBI* interest rate increase while *USGG5YR* decreases. The two graphs on the right hand side top corner in Figure 3.1.19 depict the performances of *ITRROV* and *EMBI* indexes within the period of 20.11.2001 – 05.12.2001. The shadowed frames indicate the mentioned above Flight-to-Quality window: 26.11.2001 – 30.11.2001. The bottom graph shows the respective changes in the total returns of *ITRROV* and *EMBI* indexes expressed in percentage of their respective values on 26.11.2001, which are +1.15% and -2.26%, respectively. Thus, subtracting the later figure from the former, the overall strength of 3.41% can be ascribed to the considered Flight-to-Quality.

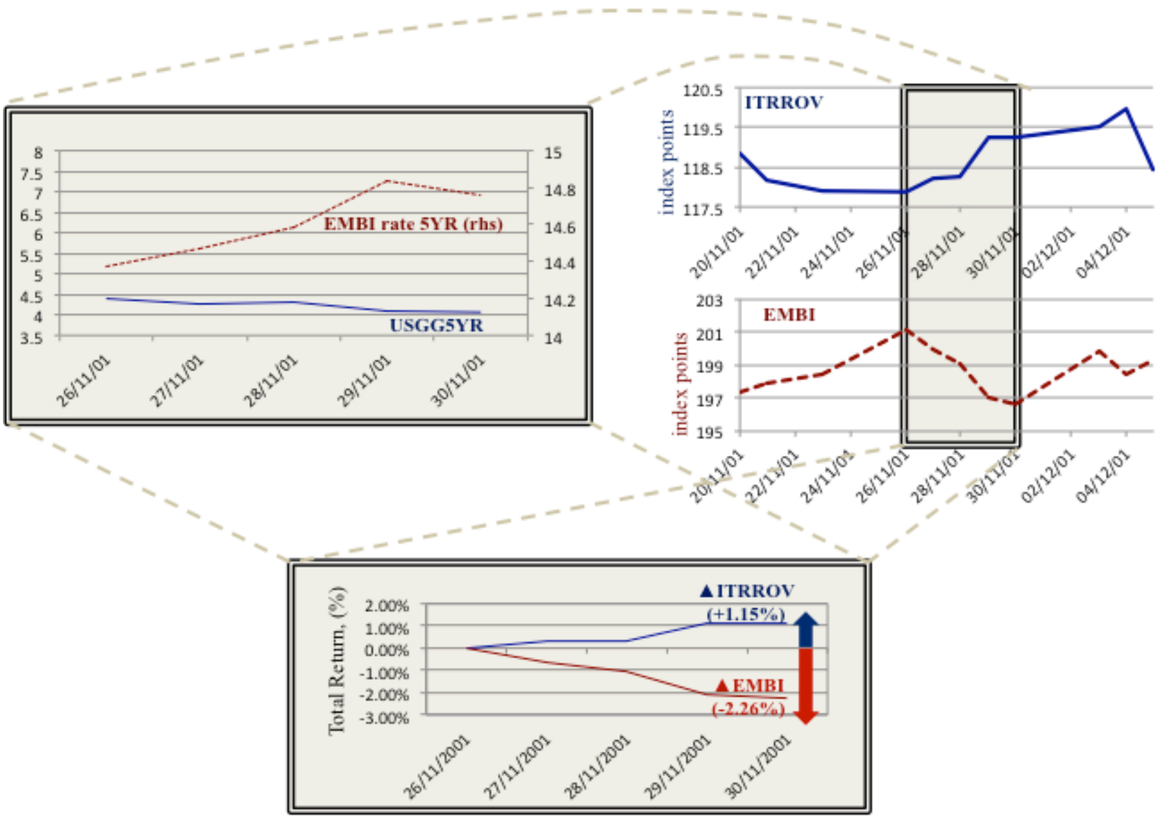



**Figure 3.1.19**: Flight-to-Quality of the *A*-subtype of the 1st type (26.11.2001 – 30.11.2001).
(*rhs* stands for right hand side scale)

<u>*Example of the 1.B–subtype of Flight-to-Quality:*</u>

The *1.B-subtype* of the 1st type of Flight-to-Quality is illustrated in Figure 3.1.20 below. It is characterized by the increasing trends in the total returns of both, *EMBI* and *ITRROV* indexes under decreasing mid-term risk-free interest rate. The chosen event happened over the period of 04.09.2007 – 10.09.2007.

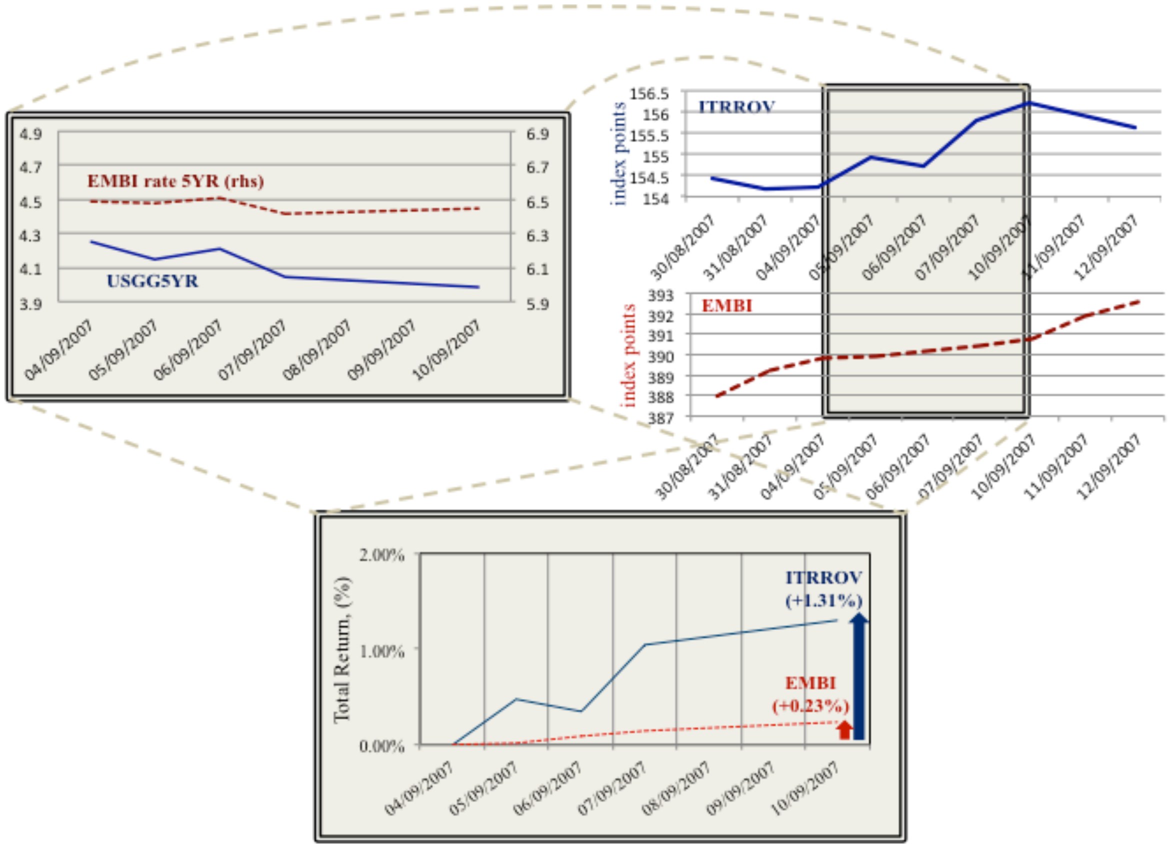



**Figure 3.1.20**: Flight-to-Quality of the *B*-subtype of the 1st type (04.09.2007 – 10.09.2007).
(*rhs* stands for right hand side scale)

The graph on the top of the left hand side in Figure 3.1.20 illustrates the dynamics of *USGG5YR* and the dynamics of the *EMBI*-subjacent interest rate calculated as a sum of *USGG5YR* and converted to percentage points *JPEMSOSD* indexes, measured by the ordinate scale on the right hand side (*rhs*) of the chart.

The graph on the top of the left hand side in Figure 3.1.20 depicts the decrease in *USGG5YR* by 0.27 p.p. while the *EMBI*-subjacent interest rate decreases only by 0.05 p.p. within the analyzed Flight-to-Quality window 04.09.2007 – 10.09.2007. As a result, the increase in the *EMBI* performance is considerably weaker than in the *ITRROV* returns. The two graphs on the right hand side top corner in Figure 3.1.20 depict the performances of *ITRROV* and *EMBI* indexes within the period of 30.08.2007 – 12.09.2007. The shadowed frames indicate the mentioned above Flight-to-Quality window 04.09.2007 – 10.09.2007.

The bottom graph shows the respective percentage changes in the total returns of *ITRROV* and *EMBI* indexes from the beginning to the end of this Flight-to-Quality, which are +1.31% and +0.23%, respectively. This corresponds to the overall strength of this event of 1.08%.

*Example of the 2nd Type of Flight-to-Quality:*

Figure 3.1.21 depicts an empirical example of the 2nd type of the proposed Flight-to-Quality typology. It is characterized by the decreasing trends in the total returns of both, the risky *EMBI* and safe *ITRROV* indexes under increasing mid-term risk-free interest rate. The chosen event occurred over the time interval of 13.04.2004 – 10.05.2004. The top graph on the left hand side of Figure 3.1.21 illustrates the dynamics of *USGG5YR* and the dynamics of the *EMBI*-subjacent interest rate calculated as a sum of *USGG5YR* and converted to percentage points *JPEMSOSD* indexes measured by the ordinate scale on the right hand side (*rhs*) of the chart.

The graph on the top of the left hand side in Figure 3.1.21 depicts the increase in *USGG5YR* by 0.56 p.p. while the *EMBI*-subjacent interest rate increases by 2.14 p.p. within the considered Flight-to-Quality window 13.04.2004 – 10.05.2004. As a result, the decline in the *ITRROV* performance is considerably weaker than in the *EMBI* returns. The two graphs on the right hand side top corner in Figure 3.1.21 depict the performances of *ITRROV* and *EMBI* indexes within the period of 01.04.2004 – 20.05.2004. The shadowed frames indicate the mentioned above Flight-to-Quality window 13.04.2004 – 10.05.2004. The bottom graph of Figure 3.1.21 shows the respective percentage changes in the total returns of *ITRROV* and *EMBI* indexes from the beginning to the end of this Flight-to-Quality, which are -2.05% and -9.64%, respectively. Thus, the total impact of this Flight-to-Quality is 7.61%

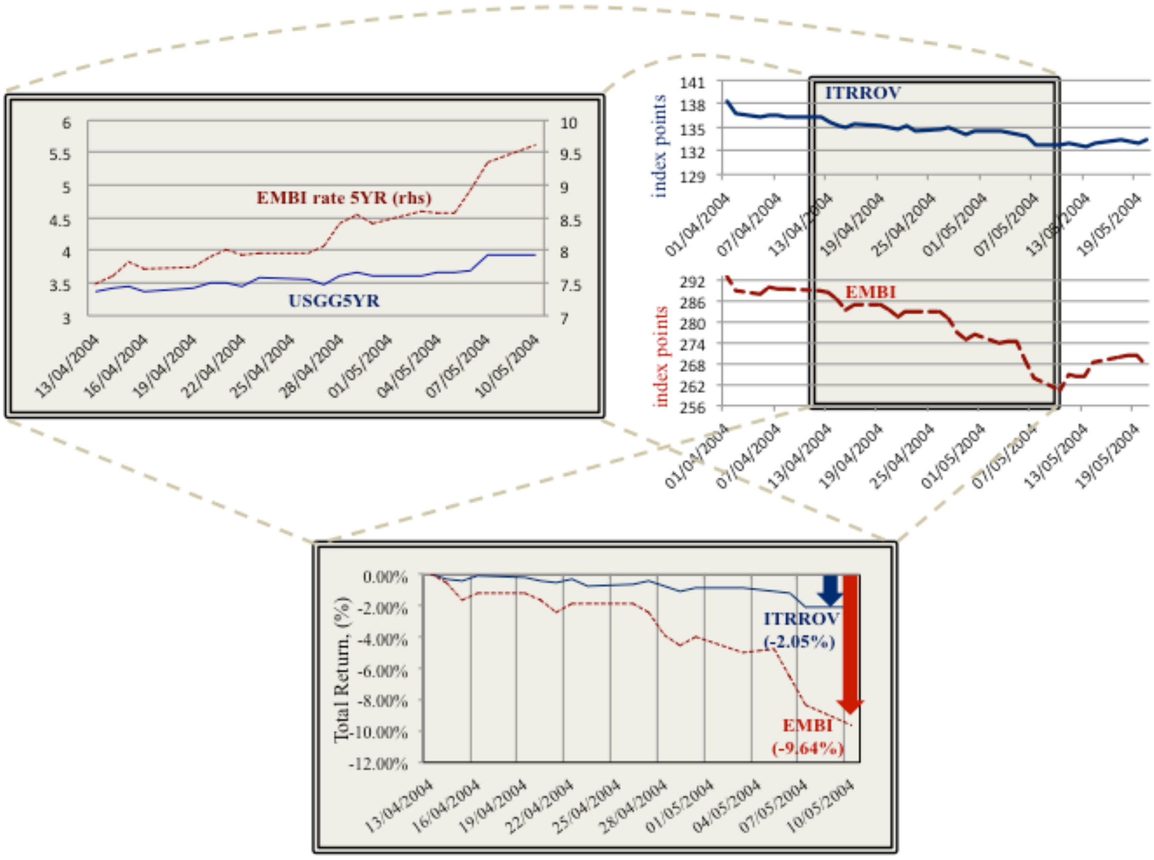



**Figure 3.1.21**: Flight-to-Quality of the 2nd type (13.04.2004 – 10.05.2004).
(*rhs* stands for right hand side scale)

*Economic Interpretation of the Flights-to-Quality over 1998 – 2010*:

The Flights-to-Quality occurred over the 1998 – 2010 are depicted in Figures 3.1.22 – 3.1.27 below according to the proposed, in the section 3.1.1.2, typology of Flight-to-Quality.

In order to characterize the periods of global economic slowdown (including contraction) and the phases of global economic growth within the analyzed period, the historical behavior of the U.S. Generic government rate at 5-year maturity (*USGG5YR*) is considered (see Figure 3.1.22, 3.1.24, and 3.1.26). Additionally, along with *USGG5YR* index, the differential *EM* spread index *JPEMSOSD* is taken into account to analyze a specific *EM* dynamics.

The decreases of the *USGG5YR* can be associated with the periods of global economic slowdown. On the contrary, under economic growth conditions the increase in inflation rates and, hence, in risk-free interest rates is expectable.

On the other hand, the increases in *JPEMSOSD* are likely to indicate phases of *EM* distress and aversion. The flight of investment out of *EM* and resulting decrease in *EM* securities performance can be attributed to the increase in the demanded risk premium, i.e. spreads over the risk-free asset yields, as captured by the increases in the index *JPEMSOSD* representing the differential spread of *EM* debt over *UST* bonds.

In parallel, there are presented Figures 3.1.23, 3.1.25, and 3.1.27, which demonstrate the relationship between the occurrences of the *1.A-subtype*, *1.B-subtype*, and the *2$^{nd}$ type* of Flight-to-Quality, respectively, and the economic growth rates. The U.S. and the World annual *GDP* growth rates according to the World Bank data are considered for this analysis.

Flights-to-Quality of *1.A-subtype*, characterized by a drop in *EMBI* accompanied by an increase in *ITRROV* returns, are depicted in Figure 3.1.22 by the lines of the same height, which are used only to indicate the initial dates of the Flight-to-Quality occurrences without any relation to the strengths of the events. The major concentrations of Flights-to-Quality of *1.A-subtype* can be observed over the periods of the global economic slowdown, i.e. extended decreases in *USGG5YR*, accompanied by the strengthening of *EM* risk aversion, i.e. increases in *JPEMSOSD*. Within the analyzed period 1998 – 2010, those phases could be associated with 1998 (Russian bond default and other *EM* distresses); the first half of 2000 (Dotcom crash); 2001 – 2002 (September 11 Attack and War on Terror, Brazil presidential election uncertainty), and the second quarter of 2007 – 2010 (U.S. subprime mortgage crisis ignition resulting into the Global Financial Crisis). In graphical terms, these periods could be recognized by higher density of individual events making separate event lines appear like the shadowed frames.

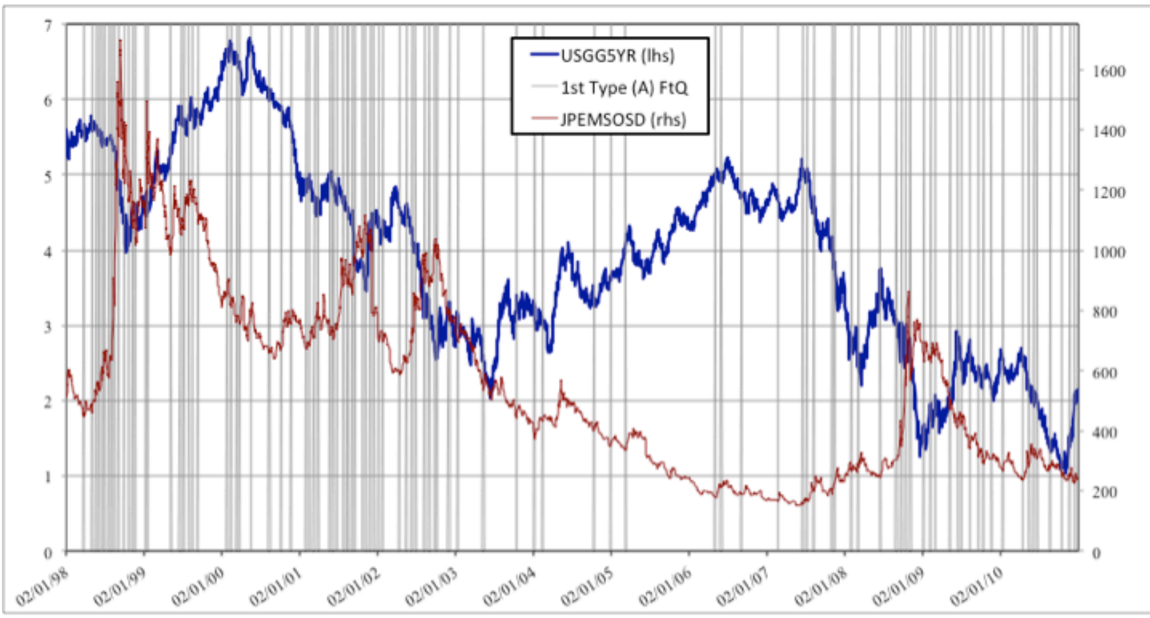



**Figure 3.1.22:** Occurrences of the Flights-to-Quality of the 1st Type, Subtype A, along with the USGG5YR and JPEMSOSD index behavior over 1998 – 2010.
(*rhs* stands for right hand side scale and *lhs* stands for left hand side scale)

In order to illustrate the given economic interpretation of the *1.A-subtype* of Flight-to-Quality, the Figure 3.1.23 below depicts the relationship between the occurrences of these events and the U.S. and the World economic growth rates.

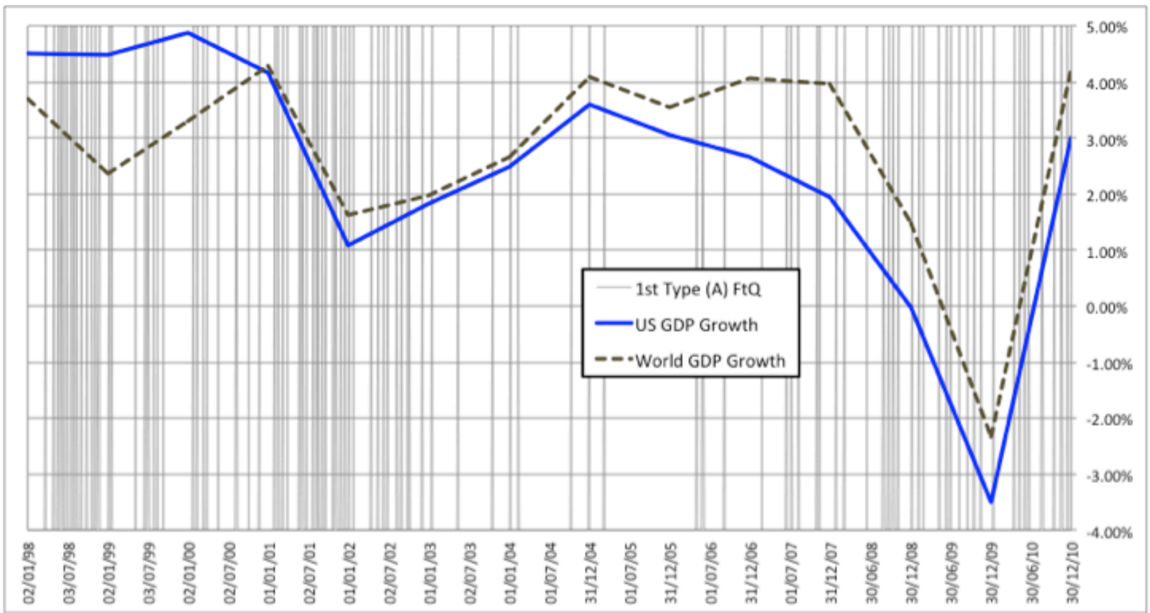



**Figure 3.1.23:** Occurrences of the Flights-to-Quality of the 1st Type, Subtype A, along with the U.S. and the World annual GDP growth rates over 1998 – 2010.

As expected, the higher frequency of the *1-A subtype* of Flight-to-Quality coincides with the decreasing slope of the *GDP* growth rate curves, especially so in case of the World *GDP* (see year 1998).

*Flights-to-Quality of 1.B-subtype*, characterized by the simultaneous increase both, in the *ITRROV* and *EMBI* indexes´ returns, are depicted in Figure 3.1.24 below by the lines of the same height, which are used only to indicate the initial dates of the Flight-to-Quality occurrences without any relation to the strengths of the events.


**Figure 3.1.24:** Occurrences of the Flights-to-Quality of the 1st Type, Subtype B, along with the USGG5YR and JPEMSOSD index behavior over 1998 – 2010.
(*rhs* stands for right hand side scale and *lhs* stands for left hand side scale)

Flights-to-Quality of *1.B-subtype* happen when the slides in *USGG5YR* coincide with decreases in the *EMBI*-subjacent interest rate, which is calculated as a sum of the *USGG5YR* and expressed in percentage terms *JPEMSOSD* indexes. These events are relatively rare: only 11 out of 133. The interpretation of this fact is provided further on in this section. Their major concentration is observed within September 2007 – August 2008 time interval, representing a kind of switching from the phase of the economic growth to the economic contraction, accompanied by the strengthening believe of the investors about the end of the era of the economic expansion. It is worth noting that the time interval of September 2007 – August 2008 marks a year long period preceding the credit crunch in September 2008.

Thus, one can conclude that Flights-to-Quality of *1.B-subtype* happen around the turning points, which are characterized by the initial doubts of the market participants regarding the continuation of the economic expansion. Additionally, these events can be considered as a useful hints or the alarm signals warning of further decline in the risk-free interest rates. It is worth noting that in all the cases, considered in this study, they are followed by local minima of the mid-term risk-free rate (*USGG5YR*), with their values being inferior to those of the end dates of the Flights-to-Quality of *1.B-subtype*.

In order to illustrate the given economic interpretation of the *1.B-subtype* of Flight-to-Quality, the Figure 3.1.25 below depicts the relationship between the occurrences of these events and the U.S. and the World economic growth rates.

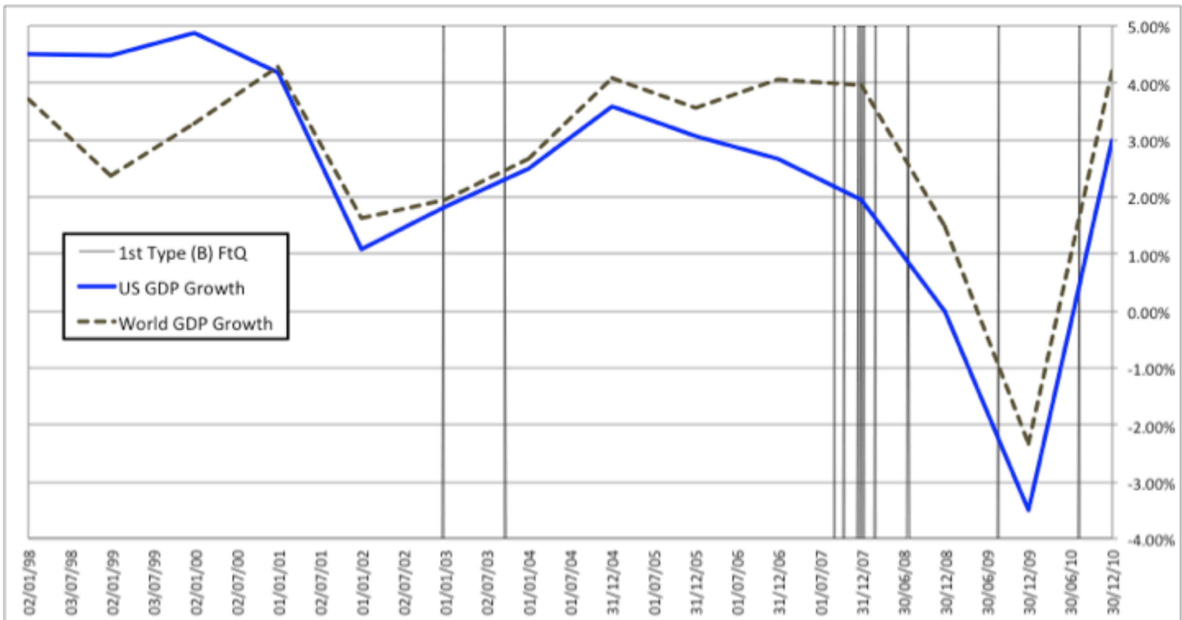



**Figure 3.1.25:** Occurrences of the Flights-to-Quality of the 1st Type, Subtype B, along with the U.S. and the World annual GDP growth rates over 1998 – 2010.

As expected, the major concentration of the *1-B subtype* of Flight-to-Quality coincides with the turning point when the accentuated slowdown of the *GDP* growth rate curves begins, especially so in case of the World *GDP* (see 2007 - 2008).

*Flights-to-Quality of the* $2^{nd}$ *type*, characterized by the simultaneous drop both, in *ITRROV* and *EMBI* returns, are depicted in Figure 3.1.26 by the lines of the same height, which are used only to indicate the initial dates of the Flight-to-Quality occurrences without any relation to the strengths of the events. The major concentrations of the second type phenomena could be observed over the periods of global economic expansion (i.e. extended increases in *USGG5YR*), which are accompanied by the long-run weakening of *EM* risk aversion, i.e. decreases in *JPEMSOSD*. Of course, the proper Flights-to-Quality are but the short-run inversions of this long-run *EM* tendency being exactly the intervals of the relative increases in *EM* risk aversion. Note that within these intervals the *EMBI*-subjacent interest rate suffers a higher growth than the risk-free *USGG5YR*. This happens due to the increase in *JPEMSOSD*. Generally, within the analyzed period 1998 – 2010, the phases could be associated with 1999 and 2000 (Technological bum); 2003 – 2007 (global economic expansion and the *EM* growth), and the last quarter of 2010 (partial recovery from the Global Financial Crisis).


**Figure 3.1.26:** Occurrences of the Flights-to-Quality of the 2nd Type along with the USGG5YR and JPEMSOSD index behavior over 1998 – 2010.
(*rhs* stands for right hand side scale and *lhs* stands for left hand side scale)

In order to illustrate the given economic interpretation of the *2nd type* of Flight-to-Quality, the Figure 3.1.27 below depicts the relationship between the occurrences of these events and the U.S. and the World economic growth rates.

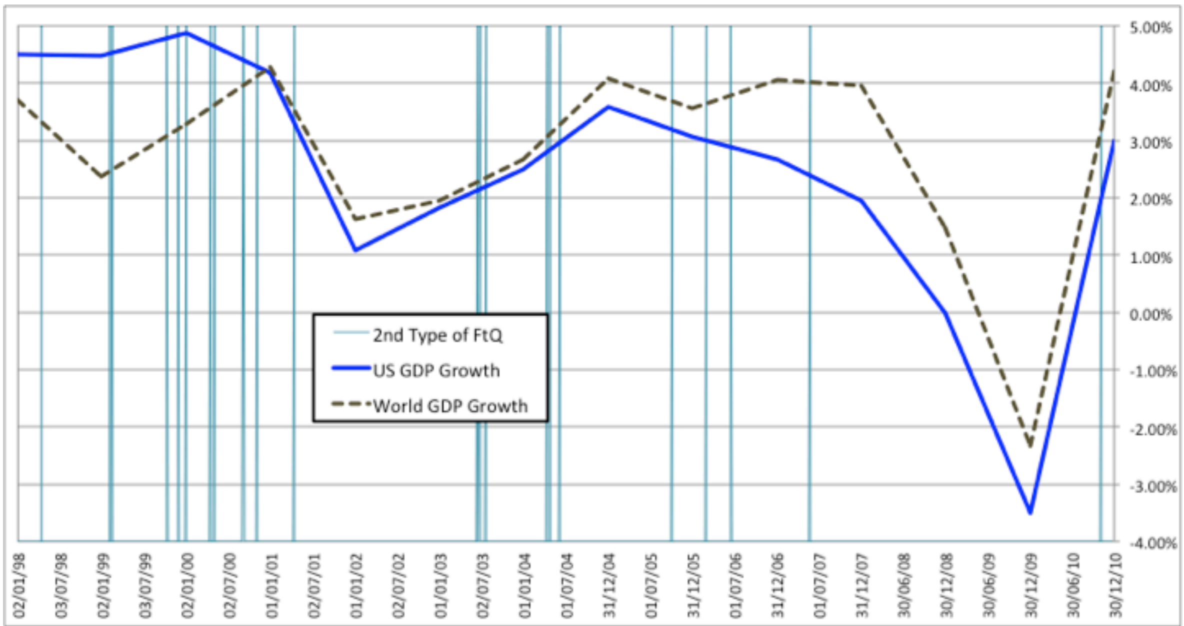



**Figure 3.1.27:** Occurrences of the Flights-to-Quality of the 2nd Type along with the U.S. and the World annual GDP growth rates over 1998 – 2010.

As expected, the major concentration of the *2nd type* of Flight-to-Quality coincides with the increasing slope of the *GDP* growth rate curves, especially so in case of the World *GDP*.

In order to comprehend the frequency of the Flights-to-Quality of each type/ subtype, the Table 3.1.17 below represents the analyzed occurrences happened over 1998 – 2010 in accordance with the nature of their typology.

| 1st type of Flight-to-Quality | | 2nd type of Flight-to-Quality |
|---|---|---|
| A Subtype | B Subtype | 22 |
| 100 | 11 | |

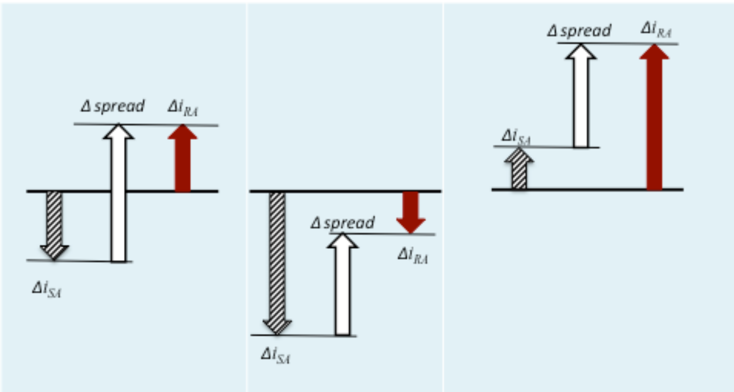



**Table 3.1.17**: The number of Flights-to-Quality by typology happened within 1998-2010.

As can be concluded from this Table, the least frequently observed type of Flight-to-Quality is the *1.B-subtype*, which accounts only for 11 out of the total of 133 Flight-to-Quality occurrences. The *1.B-subtype* events represent just 8% of the studied sample. On the contrary, the *1.A-subtype* is the most common typological class and represents 75% or the three fourths of the total number of the occurrences. In its turn, the *2nd type* accounts for the rest of 17% of the totality of the occurrences and, thus represents a rather rare type of Flights-to-Quality while compared to the frequency of the *1.A-subtype* occurrences.

This distribution of the events among the typology classes can be comprehended through the following logic. Any type of Flight-to-Quality event is but a (mini)-crisis situation. In its turn, the phenomena of the *1st type,* according to the proposed typological classification occur within the periods of the decrease in risk-free interest rates. These periods usually coincide with the phases of financial turmoil and economy distress. The latter are revealed through or represent by themselves the proper Flight-to-Quality events. So, it is expectable that the number of the *1st type* events must be considerably higher in comparison with the *2nd type* of the Flight-to-Quality, as it is: 111 events belonging to *1st type* versus only 22 events of the *2nd type*.

This is because the events of the *2nd type* happen along increasing trends in risk-free interest rates, which usually accompanies the periods of the economic prosperity, where probability of crisis to happen is low and the Flight-to-Quality of the *2nd type* can be seen as a temporary and rare reevaluations of the investors' expectations.

In respect to the relatively low frequency of the *1.B-subtype*, it can be comprehended through the following considerations. The fact, that under this *1.B-subtype* the risky assets exhibit positive returns, means that aversion towards the risky assets does not cause the sufficient widening of the spread to overcome the positive impact on their performance from the decrease in the risk-free interest rates. Such episodes by the present study are ascribed to the initial worries of the investors regarding the overall state of the economy as they coincide with switches between expansion and slowdown phases and vice-versa.

## 3.2. Setting up the Model of Flight-to-Quality

The proposed model of the Flight-to-Quality origins is based on the concept of sectoral shifts in investment preferences. The general idea of this approach is formulated in Black (1987). The author stresses the importance of significant investment reallocations across economy sectors occurring along the business cycle. Taking these inter-sectoral flows of investment into consideration allows better comprehension of the nature of a coming economic crisis. In the present research the concept of sectoral shifts is applied to describe the origins of Flight-to-Quality, i.e. mini-crisis. Considering the limit case of only two sectors, namely the real economy (risky investments) and the governmental custody (safe investments), – the interrelation between the respective risk appetites is analyzed. Particularly important are time intervals of a sudden massive withdrawal of funds from the risky sector in favor of the safe custody, which are the proper Flight-to-Quality occurrences.

The fact that the proposed model treats the investment universe as consisting of the two distinct domains, safe and risky, allows the dynamics of the investors´ appetites for risky and for safe assets to be focused on. Here the concept of an asset appetite stands for a willingness to hold a chosen type of financial assets. For example, an appetite towards risky instruments, commonly called risk appetite, makes investors hold riskier assets instead of safe securities. Similarly, the appetite for safe assets, widely perceived as risk aversion, expresses investors´ preferences for less risky investments.

To quantify investors´ appetites for both the risky and safe assets classes, the model analyses the dynamics of the respective total return indexes. The comparison of the asset classes´ performances over the same time intervals, on the base of their total returns, allows decipher indications of upcoming sharp changes in the risk attitudes which accompany

Flight-to-Quality. To make the risk-related features more explicit, the proposed model separately studies the impact of the risk-free interest rates on security prices. Decomposing the analyzed total returns into the global generic (risk-free interest rate) and investment specific (risk premium) components, allows for quantifying of investors´ appetites for safe and risky assets.

This part is structured as follows. In the first section, the dual model of the investment universe is developed as a basis for the Flight-to-Quality studies. Based on this, an approach to quantify investors´ appetites for risky and safe assets is proposed. The employed method derives investors´ asset appetite values from the historical dynamics of total return indexes as proxies for the behavior of safe and risky asset baskets. As the return patterns and, consequently, the appetites for the safe and risky asset classes differ considerably, a special adjustment of returns to the same level of subjacent riskiness is introduced for distilling comparative investors´ preferences.

In the second section, three specific metrics are proposed for measuring asset appetites related parameters. By construction, these three metrics are not affected by risk-free interest rate changes, being, thus, purely influenced by investment specific risk appetite, i.e. risk premium and risk aversion. The *S*afe *A*sset *A*ppetite (*SAA*) quantifies an aggregated appetite existing in the system to hold safe assets while the *E*xpectation-adjusted *R*elative *A*ppetite (*ERA*) represents a risky component of the overall asset appetite in the system. The latter is but a quantified preference to hold risky assets in comparison to safe securities. The *E*xpectation-adjusted *C*umulative *A*ppetite (*ECA*) is a pure measure of the total investors' appetite for all the financial assets of the modeled investment universe. The cumulative appetite dynamics also proves to be insightful for comprehension of Flight-to-Quality occurrences.

### 3.2.1. Dual Model of the Investment Universe: Safe and Risky Assets Domains

In order to analyze the nature of Flight-to-Quality, the model considers the simplified investment universe, represented by the safe and risky domains as schematized in Figure 3.2.1. On one hand, based on the assumption of the safe haven status of the top-rated government bonds, for example *UST* bonds, this type of assets is proposed to represent the safe domain of the modeled investment universe. On the other hand, the risky part of the investment universe can be represented by Emerging Market debt, and/ or other high-risk debt issues as, for example sovereign debt issues of distressed peripheral European countries, corporate high yield debt known as junk bonds, etc.

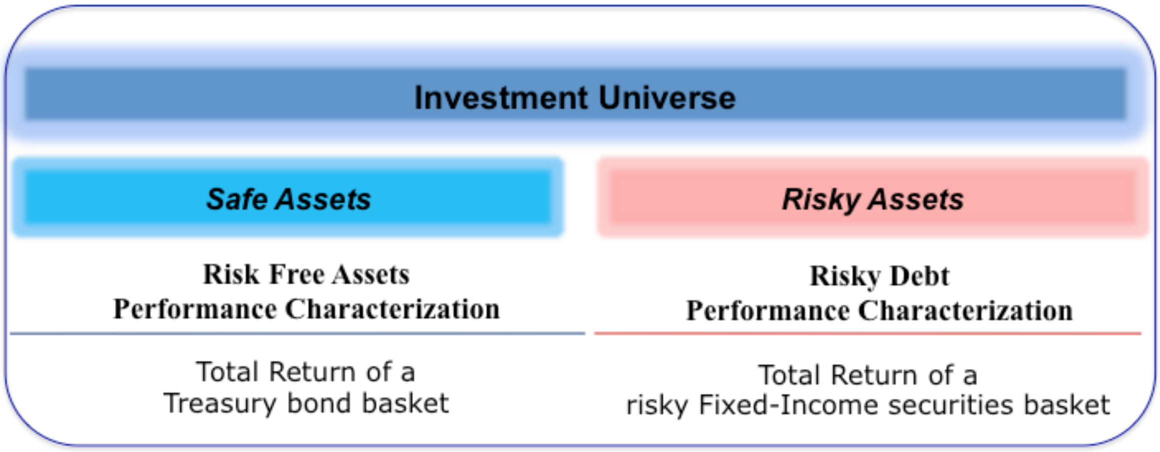



**Figure 3.2.1**: Representation of the modeled investment universe.

As schematically suggested in the Figure above, the returns of risk-free and risky assets are used to characterize the performance of the two parts of the investment universe, also enabling quantification of the return on investment of the whole model universe. It is worth noting that the performance metrics depend on the concrete selection of the securities chosen to build the safe and the risky asset baskets.

If considered through the prism of its consequences, in general terms a Flight-to-Quality can be interpreted as a phenomenon of a quick value-creation in the safe part of the "*risky* + *non-risky*" investment universe accompanied by the corresponding relative value destruction in its risky part. This is a result of sharp changes in the asset appetites. Thus, the asset appetites dynamics regarding the two parts of the modeled investment universe, prior to and in proper times of Flight-to-Quality, is essential for the analysis of these phenomena.

The asset appetite dynamics within the modeled investment universe can be briefly described as follows. Investors, flying from risk, avoid the riskiness of less secure assets by choosing the safe haven top-rated government bonds with relatively low yields. On the contrary, in order to be rewarded for the risk-taking by investing in riskier instruments, investors expect returns to be higher than those from the safe assets. Due to the continuous changes in demand for each asset class, their prices and returns vary along the time. These dynamics are influenced by the investors´ expectations, which have a different nature depending on a considered asset class.

As explained in the following sub-section, it is already a well established academic and industry practice to employ an aggregate description of expectations by the two widely used parameters: the risk-free interest rate, representing global generic expectations regarding future states of economy (and inflation rates) and the spread or risk premium, representing specific investors´ expectations regarding a chosen investment with uncertainty of receivables.

#### 3.2.1.1. Safe and Risky Assets Value Drivers: Risk-Free Interest Rate and Risk Premium

The logic applied by the proposed model to describe the dynamics of market expectations is similar to the Keynes's (1936) thoughts expressed in the Chapter 12 entitled "*The State of Long-Term Expectation*" of his book "*The General Theory of Employment, Interest and Money*". According to him, investors usually evaluate investment projects on a base of the future cash flows, which they expect their investment to generate in times still to come. The present value of future cash flows depends on the future riskiness or possibility of default of receivables and future interest rates changes, which cannot be known a priori. Consequently, for the analysis of the investment opportunity investors define the likelihood of payments and interest rates based on their expectation of what these future values should be. Investors' expectations are usually based on such factors as, for example, investment resilience considerations, human behavior, political and social atmosphere, etc., i.e. information available at that moment when this analysis is being performed.

For example, in a simple case, an investment opportunity analysis could be represented by the present value estimation of the future cash flows of a risk-free U.S. Treasury bond. As the notional values of the coupon payments and the amortization of the principal are known and unchangeable (due to the risk-free status equal to the non-default assumption), the only factors, which influence the present value of the safe haven bonds, are risk-free interest rates. Hence, the present value (*PV*) is determined by the discounted future cash flows being just its coupon payments and principal amortizing. This can be expressed as follows:

$$PV = \sum_{n=1}^{N} \frac{CFN_n}{\left(1+i_n\right)^{T_n}}, \tag{3.2.1}$$

where $PV$ is a present value;

$CFN_n$ is the cash flow notional of the $n^{th}$ payment;

$i_n$ is a risk-free interest rate, corresponding to the term $T_n$.

Usually $i_n$ and $T_n$ are expressed on an annual basis.

Thus, the uncertainty of the addressed here risk-free investment opportunity enters in the formula above only through the denominators. From the economic point of view, the uncertainty is present as the interest rates considered for the investment analysis today could differ from the interest rates which in fact will take place in the future. In this sense, the uncertainty here is linked to the interest rates projected into the future, which in their turn are based on the investors' expectations of the future economic conditions and inflation rates. This type of uncertainty could be interpreted as the risk-free interest rate-related uncertainty (an uncertainty related to the generic risk-free interest rate expectations). The historical data series evidence a direct comprehensible relationship between the U.S. generic interest rate dynamics and the total returns of risk-free *UST* bonds. Total returns of the *UST* bonds basket increase when the U.S. interest rates drop and vice versa. From this point of view, for the purpose of the proposed model of the investment universe, the *UST* behavior is considered to be free of any other investment specific risk (for example, possibly defaults in *EM* basket) and determined by the generic interest rate term structure representing a general state of the overall market expectations.

In their turn, risky (*EM*) bonds, if they were completely determined only by the interest rate considerations, should always accompany risk-free (*UST*) investment performance. But it does not happen due to the reasons explained below.

Once again, from the investment theory fundamentals follows that the bond price is nothing but a bond's present value (*PV*), which is determined by the discounted future cash flows being just its coupon payments and principal amortizing. But this time the formula differs from the previously considered due to the appearance of a so-called spread parameter:

$$PV = \sum_{n=1}^{N} \frac{CFN_n}{\left(1 + i_n + SPREAD_n\right)^{T_n}}, \tag{3.2.2}$$

where $PV$ stands for the present value;

$CFN_n$ is the cash flow notional of the $n^{th}$ payment;

$i_n$ is a risk-free interest rate;

$SPREAD_n$ is a risk-related spread or a risk premium of the subjacent security, corresponding to the term $T_n$.

In this case, as also in case of the risk-free bond, the uncertainty enters into the $PV$ formula only through the denominators. But as it can be seen, this uncertainty is not only the risk-free interest rate related, but also is influenced by the risk premium term structure, which depends on investors expectations regarding future conditions, specific to the investment under consideration.

Consequently, risky bond prices behavior would have the same pattern, as safe bond prices, should the premium for the risk taking be constant along the investment's life. Nevertheless it is not the case as the risk premium term structure, continually reassessed by the investors according to their expectations, varies with time.

### 3.2.1.2. Definition of the Investors´ Appetites for Safe and Risky Assets

Although the spread or risk premium is a widely used parameter for measuring and expressing riskiness of risky bonds (relative to safe securities), this metrics does not incorporate all the original information concerning safe and risky asset yields as it focuses only on the difference between them. Therefore, alternative approaches to the risk consideration are desirable. For instance, although in this study the spread-based approach is applied to the *ex-post* identification of Flight-to-Quality time windows, it gives little insight as to why and when Flights-to-Quality occur. For this reason the proposed model is based on a quantification of investors´ appetites for safe and risky assets. These asset appetites are distilled by special procedures out of total returns time series. This allows an analysis of the asset appetite dynamics for each asset class separately, as well as assessment of not only relative or comparative but also cumulative features of their behavior.

In accordance with the survey of risk-appetite indexes performed by Illing and Aaron (2005) and the European Central Bank (2007), the total return metrics, although not stay-alone, but along with other metrics, had already been used by several authors for the calculation of risk-appetite indexes. For example, treasury/ equities total returns ratios are incorporated into the *UBS* Investor Sentiment Index developed by Germanier (2003) and the Merrill Lynch Financial Stress Index proposed by Rosenberg (2003). These are two examples of so-called atheoretic, market-based indicators, which are not based on the theoretical models. On the other hand, a theory-based group of risk-appetite indicators represents such indexes as those developed by Kumar and Persaud (2002), Gai and Vause (2005), Misina (2006), and Coudert and Gex (2007), among others. All mentioned metrics address risk appetite/ risk aversion in the financial system as a whole. It is worth noting that the present research differs from the works mentioned above, by being focused on quantifying the investors´ appetite to hold a certain class of assets (*UST*, *EM* bonds, *EM* equities, etc.), and not the risk appetite in general. In other words, this study is centered on the quantified assessment of willingness to hold a chosen safe assets basket and its comparison with the same attitude towards a selected for a study basket of risky assets.

Prior to undertaking the quantification of the asset appetite (or willingness to hold an asset) from the total returns of the corresponding asset basket, it is desirable to eliminate the influence of factors with origins other than the asset appetite considerations. For instance, as the generic risk-free interest rate component affects both the safe and risky baskets returns, it is to be accounted for and removed from further analysis. An interest rate correction of time series of total return indexes transforms them into the "normalized" time series whose behavior is determined only by the investors´ appetite/ aversion towards an asset class under consideration.

A simple analogy may help to explain this procedure. Imagine, that in a railway carriage going at a full speed, inside of which there is a cyclist starting to ride a bike and a runner starting to run from one extremity of the wagon towards the other. Imagine next that one observer standing outside needs to decide who performs with greater dedication: the cyclist or the runner. To be able to resolve this task the observer must first concentrate on what happens relative to the moving carriage and not to the stationary land surface. As safe and risky assets baskets perform in the wider economic environment, affecting both of them by (many factors expressed through) macroeconomic dynamics of risk-free interest rates, an assessment of the risk-free interest rate impact helps to separate it from the total returns and focus on quantification of the asset appetite-related components.

Additionally, in order to meaningfully compare risky asset appetite against the appetite for safe assets, they must be brought to the same comparable level. The necessity of this adjustment can be comprehended by the fact that their respective returns and volatilities vary on different scales and exhibit distinct patterns. Thus, in order to accurately compare the dynamics of the asset appetites of different magnitudes, it would be desirable to make them comparable, i.e. vary with time in the similar magnitude ranges.

Following the cyclist-runner analogy, instead of directly comparing their speeds or the distances they cover, the observer will try to convert the speed of the runner to calculate his corresponding speed if he had been on a bike. This reconversion will likely to be based on the ratio of the observed speeds of the runner and the cyclist. Only after this is accomplished, the observer will compare the results, trying to answer whose dedication is greater and who performs better.

Figure 3.2.2 below illustrates the proposed decomposition of the changes in the total returns of safe and risky assets.

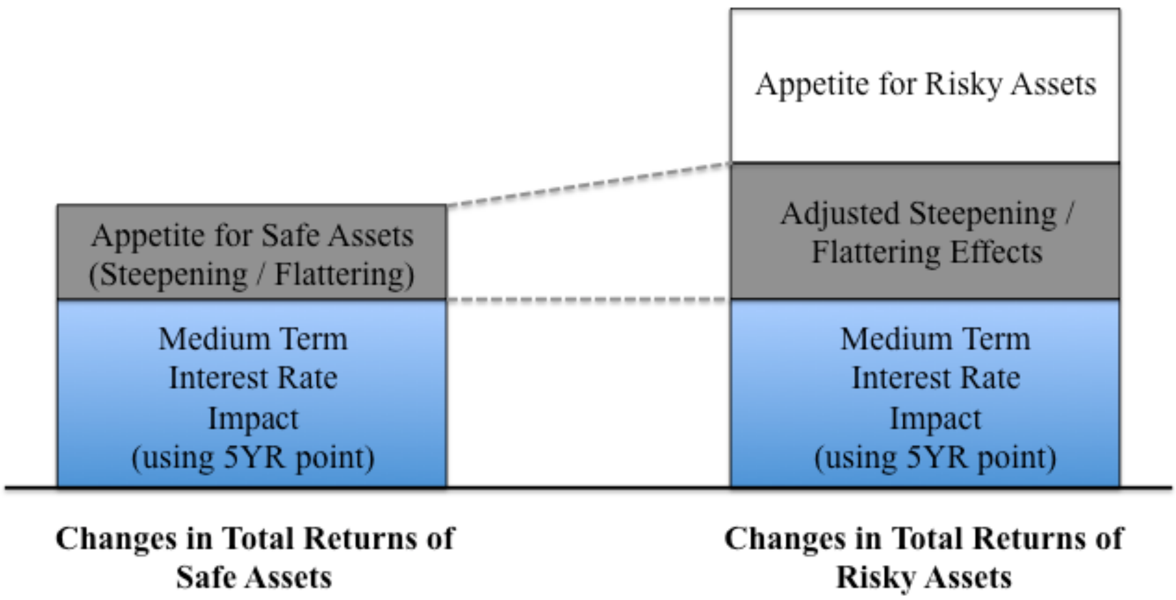



**Figure 3.2.2**: Schematic decomposition of total returns of safe and risky assets classes.

As follows from Figure 3.2.2, the model breaks down changes in the total returns of safe assets basket into the two components originated from the mid-term interest rate changes and steepening/ flattening effects. Most changes in the total returns of safe assets can be described by using a risk-free interest rate for a chosen point in the term structure, instead of employing all the rates for all the existing terms. Although the exact average maturity of the indexes is not disclosed by the index calculating companies, the point of 5 years is considered to be a good proxy as it is the most tradable, the most liquid, hence, more reliable, and the point of major interest for market makers and market participants, see for example Bunda et al. (2010). This is also consistent with the average maturity of risk-free U.S. Treasury Marketable Securities Data, which can be seen in the Quarterly Release Data issued by U.S. Department of the Treasury.

As the proposed model does not use all the interest rate values from the term structure and, for simplicity reasons, employs only the mid-term 5-year maturity effective yield, the observable effects in appetite for safe assets arise from flattening or steepening of the risk-free interest rate curve, and thus should be taken into consideration. The model interprets them as the investors' appetite for safe assets.

***Definition:***

The appetite for safe assets, regarding a certain time interval, is a difference between the total returns of the safe asset basket and the impact of the mid-term risk-free interest rate on the value of this safe asset basket, calculated over the same time interval (i.e. the *ceteris paribus* would-be returns of these asset baskets in the absence of interest rate changes).

The changes in the total returns of the risky assets basket are broken down into three components. One is the impact of the mid-term risk-free interest rate changes. The second component represents the flattening/ steepening effects of the risk-free interest rate term structure. The third component is a pure appetite for risky assets. It can be quantified by subtracting the two first components from the changes in the total returns of the risky assets basket.

***Definition:***

The appetite for risky assets, regarding a certain time interval, is a change in the total returns of the risky asset basket, liquid of the mid-term risk-free interest rate impact, and liquid of the flattening/ steepening effects of the risk-free interest rate term structure.

The proposed definitions of the investors´ appetites for safe and risky assets are applied to the construction of the asset appetite metrics. Their dynamics are used for the comprehension and delimiting of the Flight-to-Quality events on *ex-ante* basis.

## 3.2.2. Calculation Algorithm of the Asset Appetite Metrics

For the purpose of a quantitative description of the investors´ asset appetites, the model proposes three following metrics. First, the *S*afe *A*sset *A*ppetite metrics (*SAA*) is nothing but the previously defined investors´ appetite for safe assets adjusted to the level of risky assets appetite in accordance with a procedure explained further on. Second, the *E*xpectation-adjusted *R*elative *A*ppetite metrics (*ERA*) is but the previously defined investors´ appetite for risky assets. Third is the *E*xpectation-adjusted *C*umulative *A*ppetite metrics (*ECA*), which is the sum of risky and safe assets appetites.

The first step of the proposed algorithm of metrics calculation includes the interest rate correction of the total returns of the respective asset classes. The second step is an adjustment of the safe asset appetite to the level of the investors´ appetite for risky assets. The construction of these metrics is schematized below in Figure 3.2.3.

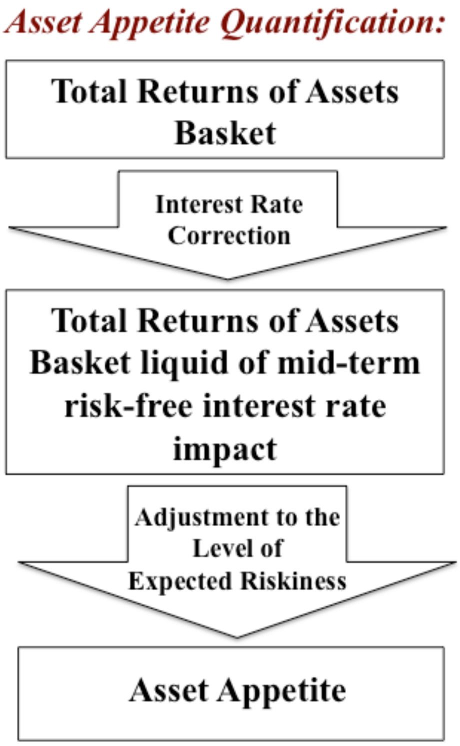



**Figure 3.2.3**: Quantification of the investors´ appetite towards an assets basket.

The interest rate correction eliminates the risk-free interest rate impact on the asset prices. The adjustment to the level of expected riskiness can be thought as of a multiplication. The asset appetite parameter, corresponding to the current level of riskiness of a certain asset class, is multiplied by the scaling coefficient, which leverages, for example, the appetite for safe assets to the level of the riskiness of risky assets, for instance *EM* bonds.

Thus, the asset appetite quantification procedure as a whole allows the appetites for different asset classes to be brought to the same expected level of riskiness and risk-free interest rate influences to be excluded. This allows a comparison of the dynamics of safe and risky assets appetites on the same magnitude basis and construction of the aforementioned *SAA*, *ERA*, and *ECA* metrics.

In order to explain how the asset appetite quantification procedure is applied to the safe and risky assets, the quantification procedure application matrix is presented in Figure 3.2.4 below.

| | Interest Rate Correction | Adjustment to the Level of Expected Riskiness |
|---|---|---|
| **Risky Assets** | Essential | Formal: multiplied by 1 as adjusted to their proper level of riskiness |
| **Safe Assets** | Essential | Essential |

**Figure 3.2.4**: Quantification procedure application matrix.

The areas of the circles on the matrix above indicate the relative importance of the steps of the asset appetite quantification procedure while applied to the safe and risky asset classes. Thus, the most important points of the application are the mid-term interest rate correction of the safe and risky assets prices and the adjustment of the safe asset appetite to the level comparable with the level of riskiness of the benchmark risky asset, such as, for example, *EM* bonds basket.

Further on in this part, the interest rate correction of total return indexes and the asset appetites adjustment procedure are discussed.

### 3.2.2.1. Risk-Free Interest Rate Component in Assets Prices and its Correction

The risk-free interest rate correction procedure is proposed in order to extract, from the time changes in total returns of safe and risky indexes, the components of the investors´ appetites, which are not related to the mid-term risk-free interest rate. These components are calculated by subtracting from the safe and risky assets total returns their respective would-be values, calculated solely on the changes of the mid-term risk-free interest rates along the analyzed time interval.

Assuming that only the risk-free interest rate can change, this procedure is based on the *ceteris paribus* condition, i.e. all other parameters remain constant. It is schematically illustrated in Figure 3.2.5 below.

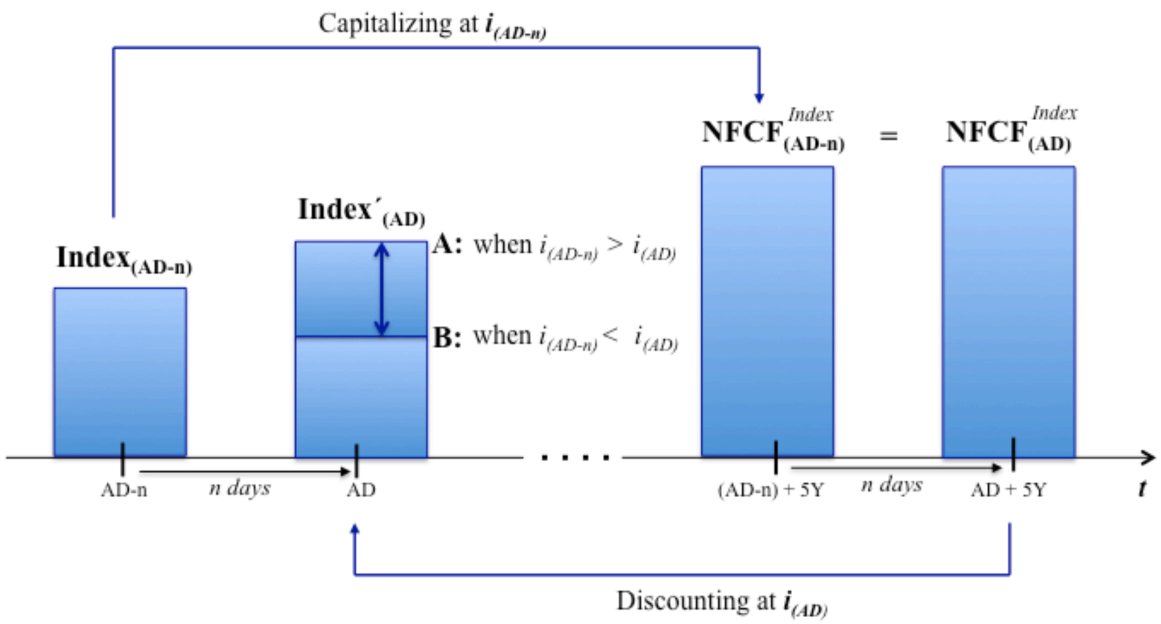



**Figure 3.2.5**: Calculation of the risk-free interest rate related changes in the index value over n-day period.

As the proposed calculations are targeting only the changes in the 5-year risk-free interest rates occurred during the time interval with the length of *n* days, the *ceteris paribus* assumption means that all other parameters remain the same over this $n$-day long interval. The future cash flow nominal corresponding to an *Index* value observed $n$ days prior to the current anchor date ($NFCF^{Index}_{(AD-n)}$) is obtained by the capitalizing procedure performed at the respective risk-free interest rate ($i_{(AD-n)}$). This value is kept unchanged and displaced $n$ days further into the future: from the point *(AD-n) + 5Y* to the point *AD + 5Y*. Then from this point *AD + 5Y*, the $NFCF^{Index}_{(AD)}$ (assumed equal to $NFCF^{Index}_{(AD-n)}$ due to the *ceteris paribus* assumption) is discounted 5 years back to the anchor date *AD* at the corresponding to this date risk-free interest rate ($i_{(AD)}$). This allows for the determination of the $Index'_{(AD)}$ would-be value, influenced only by the risk-free interest rate changes over the considered $n$-day long interval.

The proposed concept of the interest rate correction is performed following the three steps described below.

***1st Step***

The segregation of the 5-year risk-free rate impact from the total returns of the safe and risky bonds baskets, described accordingly by a safe bonds index and risky bonds index, is performed.

The respective value of the bond index, which had place $n$ days prior to the current anchor date, is capitalized going 5 years forward with the 5-year risk-free interest rate value, which it took $n$ days ago. This could be expressed by the following formula:

$$NFCF^{Index}_{(AD-n)} = Index_{(AD-n)} \times \left(1 + i_{(AD-n)}\right)^5, \qquad (3.2.3)$$

$Index_{(AD-n)}$ stands for the studied index $n$ days prior to the current anchor date (*AD*);

$i_{(AD-n)}$ is a 5-year risk-free interest rate;

*n* is a width of a time interval (going backward) expressed in working days;

$NFCF^{Index}_{(AD-n)}$ represents the nominal future cash flows, which would be received in 5-year time from the date *AD–n*, i.e. *n* days prior to the anchor date.

The formula above is simply capitalization of the asset index´s value of the day *AD–n*, i.e. the *n* days ago, also using the value of the risk-free interest rate from *n* days ago.

Then, assuming that the $NFCF^{Index}_{(AD-n)}$ is not changed over *n*-day long interval (equal to $NFCF^{Index}_{(AD)}$), its value is discounted by the 5-year risk-free interest rate of the current anchor date (*AD*). This procedure can be expressed by the following equation:

$$Index'_{(AD)} = \frac{NFCF^{Index}_{(AD)}}{\left(1+i_{(AD)}\right)^5}, \qquad (3.2.4)$$

$Index'_{(AD)}$ stands for the would-be value of chosen index on the anchor date (*AD*);

$NFCF^{Index}_{(AD)}$ is the nominal future cash flows, which would be received in 5-year time from the anchor date (*AD*) assuming that $NFCF^{Index}_{(AD)} = NFCF^{Index}_{(AD-n)}$;

$i_{(AD)}$ is 5-year risk-free interest rate, which corresponds to this current anchor date (*AD*). This equation is nothing but a discounting of the future cash flow value from 5 years in the future to the present moment (*AD*).

The above formula allows calculating of the safe and risky assets' would-be values in case when only the mid-term risk-free interest rate would change within the *n*-day time frame. Under this procedure the investors´ expectations, other than mid-term risk-free interest rate considerations, are assumed to be unchanged.

Under the proposed approach the major length of considered intervals is chosen to be 20-working days. In other words, the parameter *n* belongs to the interval [1: 20]. This time interval is consistent with the functioning of the financial markets. For instance, among others, the market uses the monthly macroeconomic data in order to determine cyclical changes in economy, see, for example, Bloom et al. (2011).

***2nd Step***

The second step consists of a comparison of the safe and risky would-be indexes´ returns corresponding to the current anchor date (*AD*) with their respective real values *n* days ago. This exercise shows what the safe and risky assets performances would be like if the only mid-term investors´ expectations regarding the development of the global economy, described by the 5-year risk-free interest rate, would change. Thus, the formula below expresses the *n*-day return of a chosen *Index* corrected by the mid-term interest rate:

$$R^{corrected}_{(AD-n,AD)} = \frac{Index'_{(AD)}}{Index_{(AD-n)}} - 1, \tag{3.2.5}$$

$Index'_{(AD)}$ stands for the would-be value of a chosen index on the anchor date obtained in the first step of interest rate correction;

$Index_{(AD-n)}$ is the real index value n days ago.

*3rd Step*

The third step is a distilling procedure, which is the subtraction from the real n-day returns of the safe and risky indexes ($R_{(AD-n,AD)}$) their respective would-be $n$-day returns ($R^{corrected}_{(AD-n,AD)}$). This can be expressed by the following equation:

$$R'_{(AD-n,AD)} = R_{(AD-n,AD)} - R^{corrected}_{(AD-n,AD)}. \tag{3.2.6}$$

This formula allows a quantification of the investors´ expectations component and, consequently, the investors' appetites, based on the returns either for safe or risky assets.

In the case of the safe assets, the short-term investors´ expectations regarding safe assets are captured. Eliminating influences of the mid-term generic expectations through the proposed interest rate correction makes more pronounced the effects of short-term changes in the risk-free interest rate term structure, which can be thought of as flattening and steepening of the interest rate curve. The positive values of $R'_{(AD-n,AD)}$ mean that the interest rate curve is flattening and, consequently, investors evaluate the future economic conditions negatively and their appetites towards safe assets increase. On the other hand, the negative values of $R'_{(AD-n,AD)}$ mean the steepening of the risk-free interest rate term structure, which shows that investors' expectations regarding future state of economy resulting from the past $n$ days are positive, which is likely to lead their safe assets exposure to decrease.

In the case of the risky assets basket, jointly, the specific investors´ expectations, related to the considered risky index performance, and the generic short-term expectations regarding the general state of the global economy are caught. Thus, the specific risk component is considered to be combined with the generic global risk component represented by the flattening and steepening of the risk-free interest rate curve. In order to address the purely risky nature of investors´ appetite for risky assets, it is necessary to eliminate the flattening-steepening effects related to the safe asset appetite dynamics. To achieve this goal, the concept of the adjustment of the investors´ appetite for safe assets to the level of the risky appetite is proposed and described further on.

#### 3.2.2.2. Adjustment of Safe Asset Appetite to the Level of Risky Asset Appetite

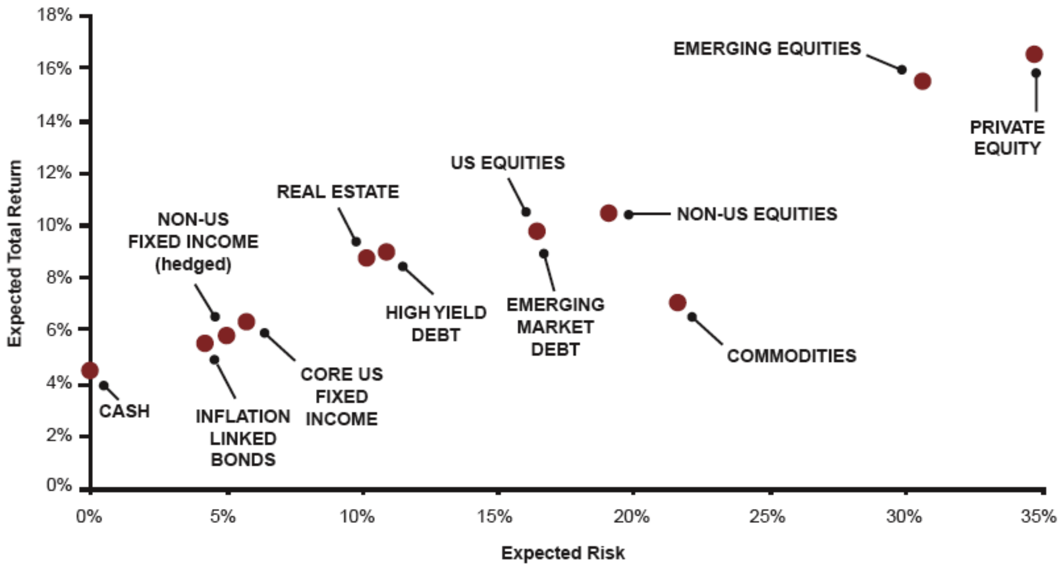
The problem of a comparison of safe asset appetite with risky asset appetite arises due to the different patterns in returns generated by the safe and risky asset classes. In order to perform this comparison meaningfully, the *E*xpectation *A*djustment *C*oefficient (*EAC*) is proposed and applied to the construction of the *SAA*, *ERA*, and *ECA* metrics.

The *EAC* coefficient originates from the concept of the expectation-adjusted investors' appetite, which is employed in order to make the differences in returns of safe and risky investments comparable, i.e. belonging to the same range of magnitude.

*EAC* allows to align the appetites for different asset classes to the same level of the expected riskiness. For the purpose of the present research, the appetite for safe assets is adjusted to the level of the appetite for risky fixed income securities.

This concept of expectation-adjusted investors' appetite is similar to the leverage-adjusted returns technique proposed by Dalio (2005) with the purpose to engineer investment portfolio with already quantitatively specified level of return, consistent with the investor's objective. Author's idea is to modify a traditional trade-off between risk and return by leveraging or deleveraging individual assets to a chosen targeted level of return, and only then to compare the return-adjusted risk parameters of assets to be included or not to the investment portfolio.

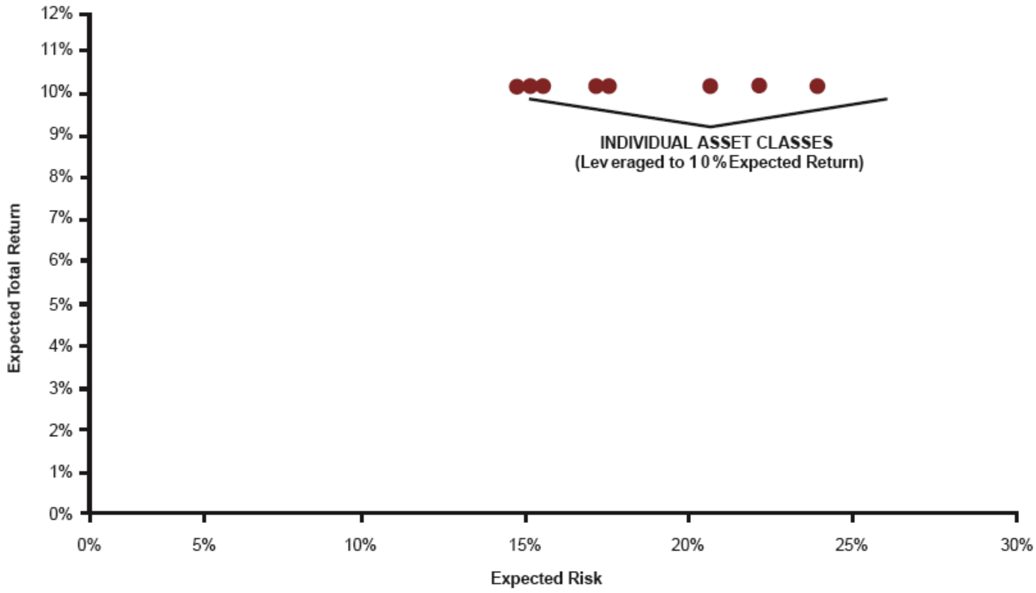
Although expected rates of assets' returns and their subjacent risk levels could differ from each other for different individuals, the major part of investors' community shares an opinion that the riskier assets are generally associated with the higher expectations of future returns as illustrated in Figure 3.2.6 below. The cause of the higher expected return being associated with the higher expected risk is a possibility to use borrowing for increasing the expected return and, consequently, the expected risk of any investment assuming an arbitrage opportunity exists. Alternatively speaking, the asset classes with higher levels of expected returns, such as, for instance, real estate, equities, and venture capital are associated with higher future returns and risks exactly due to their imbedded leverage, or leverage existing within the securities.




Sources: Dalio (2005)

**Figure 3.2.6**: Expected rates of return and expected levels of risk for diverse asset classes.

For example, as it can be seen in the Figure 3.2.6 above, the core U.S. fixed income securities are associated with lower levels of return in comparison to the U.S. equities. Assuming the existence of the possibility of borrowing cash, through the use of leverage, for example, bonds can be leveraged or, so to say, adjusted to the levels of returns comparable to those of equities. It should be considered that the use of leverage could be applied only if returns of the asset class to be leveraged exceed the costs of borrowing cash to buy more of the same chosen investment for the leveraging. So, the expected returns of diverse asset classes after leverage could be made similar. This procedure also will increase the expected risks, making them at the same time more compatible with one another. The Figure 3.2.7 presents the expected risk levels (considerably shifted to the right), of the same asset classes as Figure 3.2.6, but leveraged, in order to result in expected returns of 10%.




Sources: Dalio (2005)

**Figure 3.2.7**: Expected risk and return rates for the individual asset classes leveraged to expectation of 10% return level.

Applying the Dalio´s (2005) concept of the leverage-adjusted returns to the problem of the comparison of the investors appetites for the different asset classes, in order to explicitly isolate the component of the investors´ specific expectations regarding the considered risky investment, the safe and risky assets returns are proposed to be adjusted to the same level of the expected riskiness using an adjustment factor. Only then the difference in the adjusted outcomes is to be calculated.

In order to elaborate the adjustment coefficient allowing the investors´ appetite for safe assets to be brought to the level of the expected riskiness of the risky securities, the model analyzes the investment universe dynamics within a month (20-working days). The previously observed riskiness of an asset is taken as a proxy for the appetite to hold an asset or invest in it. The maximum length of time interval of 20-working days is employed in this research for the following reasons. This is a natural choice as people, including investors, think and act according to the calendar months. Additionally, financial institutions usually report on a monthly basis and usually make comparisons on a month-to-month basis even in between reporting dates.

The *EAC* calculation consists of the following steps.

***1st Step***

The 20-day standard deviations of the safe and risky assets performances are calculated for each current anchor date (*AD*) using the previous 20 days to determine the targeted $\sigma$ value:

$$\sigma_{(AD)}^{Index} = \sqrt{\frac{\sum_{i=AD-20}^{AD}\left(Index_i - \overline{Index}\right)^2}{20}}, \tag{3.2.7}$$

where $Index_i$ stands for the analyzed index value on the date $i \in [AD-20; AD]$;

$\overline{Index}$ is the 20-day average of the considered index values corresponding to the time interval $[AD-20; AD]$;

These standard deviations can be interpreted as average volatilities of the respective indexes within the past month.

***2^nd^ Step***

The ratio of the 20-working day averages of safe and risky assets are calculated for each current anchor date using the previous 20 days values occurred prior to the current anchor date in accordance with the following equation:

$$\frac{\overline{Index^{S}_{(AD)}}}{\overline{Index^{R}_{(AD)}}} = \frac{\dfrac{\sum_{i=AD-20}^{AD} Index_{i}^{S}}{20}}{\dfrac{\sum_{i=AD-20}^{AD} Index_{i}^{R}}{20}} \qquad (3.2.8A)$$

or this equation can be rewritten as

$$\frac{\overline{Index^{S}_{(AD)}}}{\overline{Index^{R}_{(AD)}}} = \frac{\sum_{i=AD-20}^{AD} Index_{i}^{S}}{\sum_{i=AD-20}^{AD} Index_{i}^{R}}, \qquad (3.2.8B)$$

$Index_{i}^{S}$ stands for the safe assets total returns index value on the date $i \in [AD-20; AD]$;

$Index_{i}^{R}$ is a risky securities total returns index value on the date $i \in [AD-20; AD]$.

***3^rd^ Step***

Finally, it is necessary to proceed with the calculation of the *E*xpectation *A*djustment *C*oefficient (*EAC*) itself, which is the ratio of standard deviations of the risky and safe assets multiplied by the inverse ratio of the average values of the respective indexes:

$$EAC_{(AD)} = \frac{\sigma_{(AD)}^{Index^{R}}}{\sigma_{(AD)}^{Index^{S}}} \times \frac{\overline{Index^{S}_{(AD)}}}{\overline{Index^{R}_{(AD)}}}. \qquad (3.2.9)$$

The $EAC$ value is calculated for each current date. Here the ratios $\frac{\overline{\sigma_{(AD)}^{Index^R}}}{\overline{Index_{(AD)}^{R}}}$ and $\frac{\overline{\sigma_{(AD)}^{Index^S}}}{\overline{Index_{(AD)}^{S}}}$ are the respective average-adjusted index volatilities. They represent relative measures of riskiness allowing for comparison of volatilities (representing perceived riskiness of indexes) on the same normalized basis, independent of the assets´ total returns and different ranges of the indexes´ values.

The *EAC* is an essential component for computing the *SAA*, *ERA*, and *ECA* metrics, which are used to quantify the dynamics of the safe asset appetite, investors´ specific risk appetite, and the investors´ appetite for the whole investment universe.

The *S*afe *A*sset *A*ppetite (*SAA*) metrics is calculated as follows. Firstly, the *SAA* is calculated for each, *m*-day long time interval, where $m \in$ [AD-20, AD-1]. So, for each anchor date (*AD*) there are 20 subjacent intervals with length of 1 to 20 days as shown in Figure 3.2.8 below.

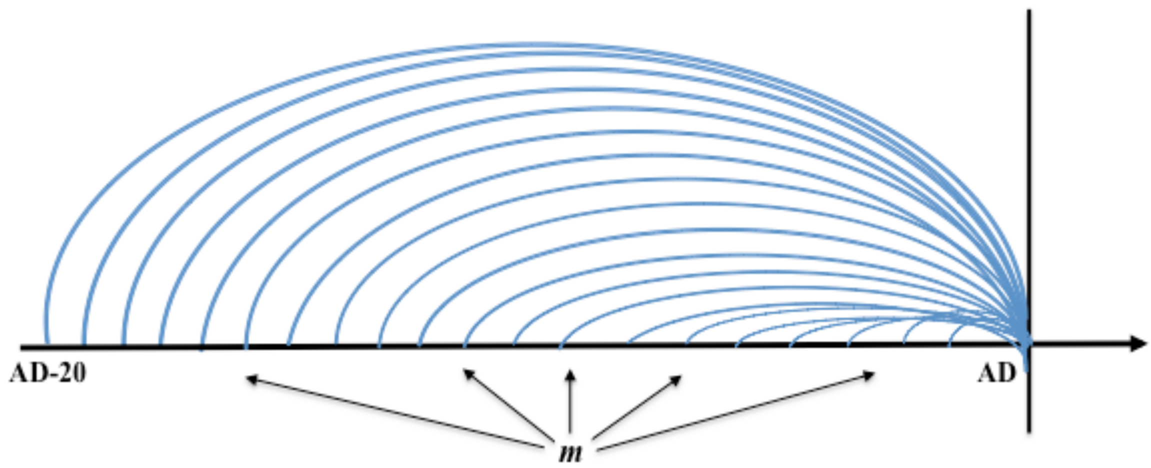



**Figure 3.2.8**: Schematic representation of time intervals used for *SAA* calculation.

According to this figure the following equation can be written for $SAA_{(m,\ AD)}$:

$$SAA_{(m,\ AD)} = EAC_{(AD)} \times R'^{S}_{(m;AD)}\,, \tag{3.2.10}$$

$EAC_{(AD)}$ is the Expectation Adjustment Coefficient corresponding to the current anchor date ($AD$);

$R'^{S}_{(m;AD)}$ is the investors´ expectations component implied by the $m$-day return of safe assets, see formula (3.2.6);

$SAA_{(m,\ AD)}$ stands for the investors´ appetite in the system to hold safe assets, adjusted to the level of riskiness of risky assets, as estimated using a chosen $m$-day long interval.

It is nothing but an interest rate corrected total return of the safe assets index multiplied by *E*xpectation *A*djustment *C*oefficient (*EAC*).

Secondly, the average value of the *SAA* is calculated over the twenty $m$-day long intervals, corresponding (laying prior) to the anchor date (*AD*):

$$SAA_{(AD)} = \overline{SAA_{(m,\ AD)}} = \frac{1}{20}\sum_{m=AD-20}^{AD-1} SAA_{(m,\ AD)}\,. \tag{3.2.11}$$

This average is calculated in order to capture the information, which indexes contain, for each day within the analyzed 20-days long interval.

In order to distill the pure specific risky assets-related component, the key *ERA* metrics is proposed and expressed by the equations below.

Firstly, the *ERA* is calculated for the each $m$-day time interval, where $m \in$ [AD-20, AD-1].

$$ERA_{(m,\,AD)} = R'^{R}_{(m;AD)} - EAC_{(AD)} \times R'^{S}_{(m;AD)}\,, \tag{3.2.12}$$

$EAC_{(AD)}$ is the *E*xpectation *A*djustment *C*oefficient corresponding to the current anchor date (*AD*);

$R'^{S}_{(m;AD)}$ is the investors′ expectations component implied by the *m*-day return of safe assets, see formula (3.2.6);

$R'^{R}_{(m;AD)}$ is the investors′ expectations component implied by the *m*-day return of risky assets, see formula (3.2.6).

Secondly, the average value of *ERA* is calculated over the twenty *m*-day long intervals, corresponding (laying prior) to the anchor date (*AD*):

$$ERA_{(AD)} = \overline{ERA_{(m,\,AD)}} = \frac{1}{20}\sum_{m=AD-20}^{AD-1} ERA_{(m,\,AD)}\,. \tag{3.2.13}$$

The *ERA* metrics can be interpreted as a quantification of the willingness of the investors community to hold risky assets liquid of or relative to the willingness to hold safe assets (with the similar average maturities).

By analogy, a calculation of the *E*xpectation-adjusted *C*umulative *A*ppetite (*ECA*) metrics is performed using the following formula:

$$ECA_{(m,\,AD)} = R'^{R}_{(m;AD)} + EAC_{(AD)} \times R'^{S}_{(m;AD)}\,, \tag{3.2.14}$$

$$ECA_{(AD)} = \overline{ECA_{(m,AD)}} = \frac{1}{20} \sum_{m=AD-20}^{AD-1} ECA_{(m,AD)} . \qquad (3.2.15)$$

The *ECA* metrics can be interpreted as a quantification of the total willingness of the investment community to hold financial (both, risky and safe) assets. This metrics is also an important measure of the considered investment universe. It characterizes the overall investors′ appetite for financial assets in the system. It is worth noting that *ECA* metrics equals to $ERA + 2 \times SAA$, where the sum $ERA + SAA$, pure risk and safe components, stands for the appetite for the risky assets, and $SAA$, safe component, is the appetite for the safe assets adjusted to the level of riskiness of risky assets.

As there are two asset classes, safe and risky, in the proposed investment universe, to make *ECA* metrics commensurable with *ERA* and *SAA* metrics, the *ECA/2* metrics will be applied further on.

This consideration finalizes the description of the *SAA*, *ERA*, and *ECA/2* metrics, which are the essential components of the Alarm Signal System to be applied in the next section to warn on coming Flight-to-Quality events and their termination dates.

## 3.3. Alarm Signal System for warning of Flight-to-Quality

The Alarm Signal System proposed in this section consists of a set of conditions, which first, warn of or coincide with the start dates of Flights-to-Quality and, second, indicate the approaching end dates of the phenomena. The Alarm Signal System is based on three metrics developed to measure and compare investors´ appetites to hold diverse assets. These three metrics are the *E*xpectation-adjusted *R*elative *A*ppetite (*ERA*), *S*afe *A*sset *A*ppetite (*SAA*), and *E*xpectation-adjusted *C*umulative *A*ppetite (*ECA/2*) metrics.

In order to warn of an upcoming event and to signal its end, the alarm system may use only the data available prior to the date at which an alarm signal is eventually to be generated. It is also a challenge in the sense that considerable changes in investors´ appetites could be provoked either by an accumulation of the impacts of consecutive weak market movements or by sharp spikes of rather impactful strength. On one hand, weak market movements continuously push the mood of the investors´ community in a certain direction, for example, increasing risk appetite, and then, already beyond a certain "acceptable" limit, they trigger an acute change in attitudes resulting in a sharp increase in risk aversion (Flight-to-Quality). On the other hand, a sudden euphoric-like positive spike in risk appetite could also be followed by a drastic backward retreat in the investors´ mood (which is also nothing but Flight-to-Quality).

This part is organized as follows. The first section proposes a set of rules to be used in the generation of alarm signals warning of Flight-to-Quality ignitions, or, in other words, entry signals. They are derived by the application of *ERA*, *SAA*, and *ECA/2* metrics to the *ITRROV* and *EMBI* indexes over 1998 – 2010.

By analogy, the second section describes the conditions of the generation of exit alarms signaling the approaching end dates of Flight-to-Quality events. They are also derived from the application of *ERA*, *SAA*, and *ECA/2* metrics to the *ITRROV* and *EMBI* indexes over the same time interval 1998 – 2010.

This part is concluded by the efficiency analysis of the proposed Alarm Signal System assessing its ability to warn of approaching flights out of *EMBI* index towards *ITRROV* index and to warn of their termination. Among others, the accuracy of the entry and exit alarms generation is examined from the point of view of comparison of the impacts of the real historically observed Flights-to-Quality and the hypothetical, entry-exit signals delimited events, i.e. would-be episodes being the outcomes of the proposed Alarm Signal System.

## 3.3.1. Generation of Entry Signals warning of Flight-to-Quality ignitions

The entry alarm signals warning of upcoming Flights-to-Quality can be separated into the three groups: *ERA* metrics upside moves, *SAA* metrics downside moves, and *ECA/2* metrics upside moves. These groups of entry signals are separately discussed and illustrated by several examples on how such warnings are generated.

### 3.3.1.1. Alarm signals based on *ERA* upside moves

Considering the *ERA* upside moves, it is implicit that not all such movements should result in the generation of the Flight-to-Quality alarm signal, but only a few of them which must be related to specific changes in asset-holding appetites. Thus, the only *ERA* upside moves, which raise this asset-holding appetite measure above the values of asset-holding appetites observed in a recent past, result in the generation of alarm signals. As there are three different asset-holding appetite metrics which are developed and used in this study, namely *ERA*, *SAA*, and *ECA/2*, the previous historical behavior of each of them can be used for comparison with the *ERA* upside moves. Thus, three different situations causing Flight-to-Quality alarm signals can be distinguished. The first is related to the alarms generated by the *ERA* upside move surpassing its proper previously observed local maximum. The second situation is the *ERA* upside move overpassing a recently observed local maximum of the *SAA* metrics. The third type of alarm is produced by an *ERA* upside move over the recent local maximum of *ECA/2* metrics.

The selection of these three cases is based on the phenomenological analysis of the historical data and additionally can be justified by the following consideration. The comparison of the *ERA* metrics to the two other metrics, namely *SAA* and *ECA/2*, is made possible by the previously described expectation adjustment procedure, which brings all these three metrics to the same level of expected riskiness making them comparable with each other.

The next exposition explains each of these three conditions in more detail and provides a set of corresponding examples.

***ERA upside move over its previously observed local maximum***

The upside move of *ERA* metrics to a level, higher than its proper recently observed local maximum, is considered an alarm signal warning of an approaching Flight-to-Quality event. This situation can be understood as follows. The local maximum of *ERA* metrics in a recent past indicates an acceptable level of investors´ optimism in terms of their willingness to hold risky assets instead of safe securities. After this level is reached, the risk appetite in the investment universe is likely to retrocede. In other words, one would expect the system to retrocede when an increase occurs in the risk asset appetites to values even higher than those previously observed. As any *ERA* local maximum indicates a turning point of risk asset-holding appetite, a new height reached by this risk appetite metrics is to be followed by a rather sharp decrease. Such *ERA* metrics dynamics, i.e. the increase in the risk appetite above its recently observed maximum, is proposed to serve as an alarm for the upcoming Flight-to-Quality event.

Additionally, the economic rational of such a turning point can be understood as follows. Investors begin to worry that the number of potential buyers of risky *EM* debt may become smaller than the number of potential sellers, thus, provoking the decrease in prices and total returns of risky assets according to the law of demand-supply equilibrium. Anticipating such situation, investors start to fly to quality of safe *UST* bonds provoking sell-off of risky *EM* assets.

In order to exemplify the *ERA* metrics upside move dynamics overlapping its previous local maximum and being a signal of the approaching event, an interval from 06.08.2001 to 04.09.2001, is chosen. The *ERA* metrics dynamics along with the behavior of the *SAA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.1.

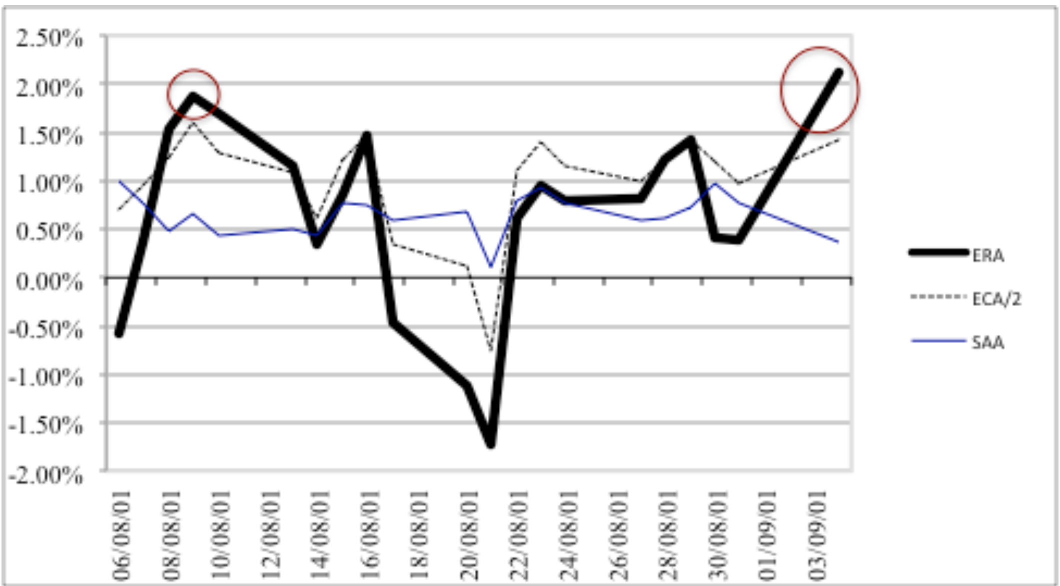



**Figure 3.3.1:** Generation of the entry alarm signal on 04.09.2001 based on the ERA metrics.

As marked by ovals in Figure 3.3.1 above, on 04.09.2001, the *ERA* metrics surpasses its previous local maximum, observed on 09.08.2001. Such a movement indicates a likely approaching Flight-to-Quality event. As can be seen in the list of the identified in 2001 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.7, the corresponding Flight-to-Quality in fact happens on 04.09.2001, the date of the appearance of the alarm signal described above.

It should be noted that the entry alarm is an indicator of the beginning of the phenomena around the date the alarm has appeared, and a temporary lag between the alarm and Flight-to-Quality can also be observed in other circumstances.

***ERA upside move over previously observed local maximum of SAA***

Signals of approaching Flights-to-Quality generated by the *ERA* metrics upside move above a recently observed maximum of the *SAA* metrics can be explained as follows. The local maximum of the *SAA* metrics is a local extreme of investors´ appetite for safe assets. When the appetite for risky assets, quantified by *ERA* metrics, overpasses the recently observed local maximum of appetite for safe assets, adjusted to the level of riskiness of the risky assets, the new height reached by the risk appetite metrics is likely to be followed by a decrease resulting in a Flight-to-Quality event.

In order to illustrate a warning alarm signal generated by the *ERA* metrics upside move overpassing the recent local maximum of the *SAA* metrics, an interval from 26.06.2008 to 03.11.2008 is chosen. The *ERA* metrics dynamics along with the *SAA* and *ECA/2* metrics within the selected period are depicted Figure 3.3.2 below.

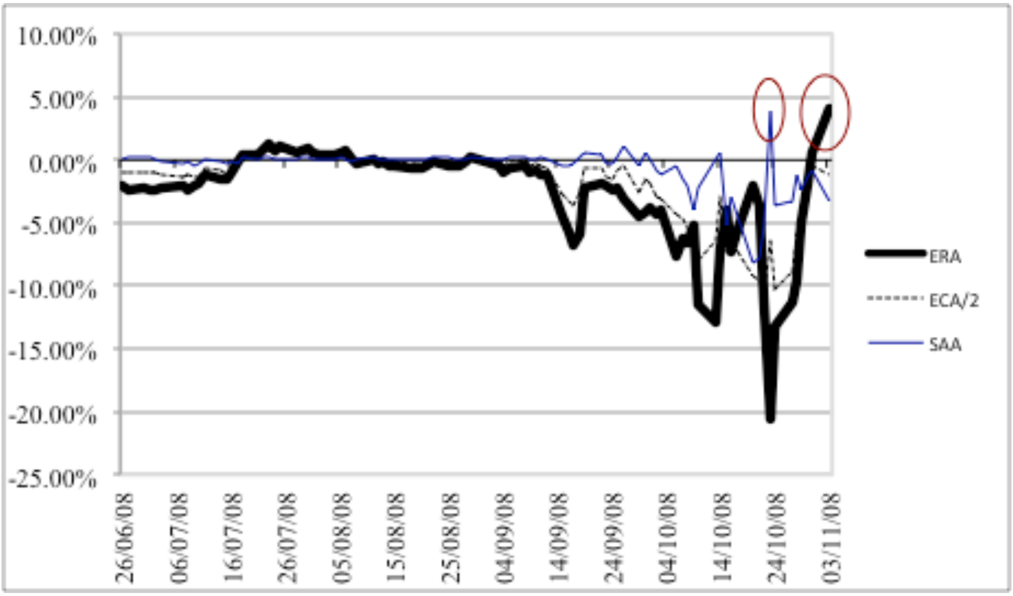



**Figure 3.3.2**: Generation of the entry alarm signal on 03.11.2008 based on the ERA over the SAA metrics.

As marked by ovals in Figure 3.3.2, the *ERA* metrics surpasses, on 03.11.2008, the recent local maximum of the *SAA* metrics, observed on 23.10.2008. Such a movement indicates the likely approach of a Flight-to-Quality event, as the recently observed maximum of (safe) asset appetite in the system is surpassed by the current level of investors´ (risky) asset appetite. It is worth noting that being adjusted to the same level of riskiness, the proposed asset appetite metrics for the risky and safe asset classes are turned to be comparable.

As can be seen in the list of the identified in 2008 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.14, the alarm signal generated on 03.11.2008, is followed by the Flight-to-Quality ignition on 04.11.2008.

***ERA upside move over previously observed local maximum of ECA/2***

The last type of signals within the class based on the *ERA* upside moves is represented by the *ERA* metrics rising above a recently observed maximum of the *ECA/2* metrics. The sense of this alarm warning of approaching Flight-to-Quality can be comprehended as follows. The *ECA* metrics represents a quantification of the aggregated investors´ appetite for both, safe and risky assets. Thus, a situation in which an increase in the appetite for risky assets, described by *ERA*, exceeds half of the recently observed maximum of the total asset appetite in the system ECA/2 (as risky assets represent half of the investment universe) could be considered a signal. This situation can be thought of as an augmentation of risk appetite over the previously formed and accepted boundary of the total investors´ willingness to invest in financial assets, which is likely to lead to risk-aversion, i.e. Flight-to-Quality.

In order to illustrate a warning alarm signal generated by the *ERA* metrics upside move overpassing the recent local maximum of *ECA/2* metrics, an interval from 03.12.2001 to 23.01.2002, is chosen. The *ERA* metrics dynamics along with the *SAA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.3.

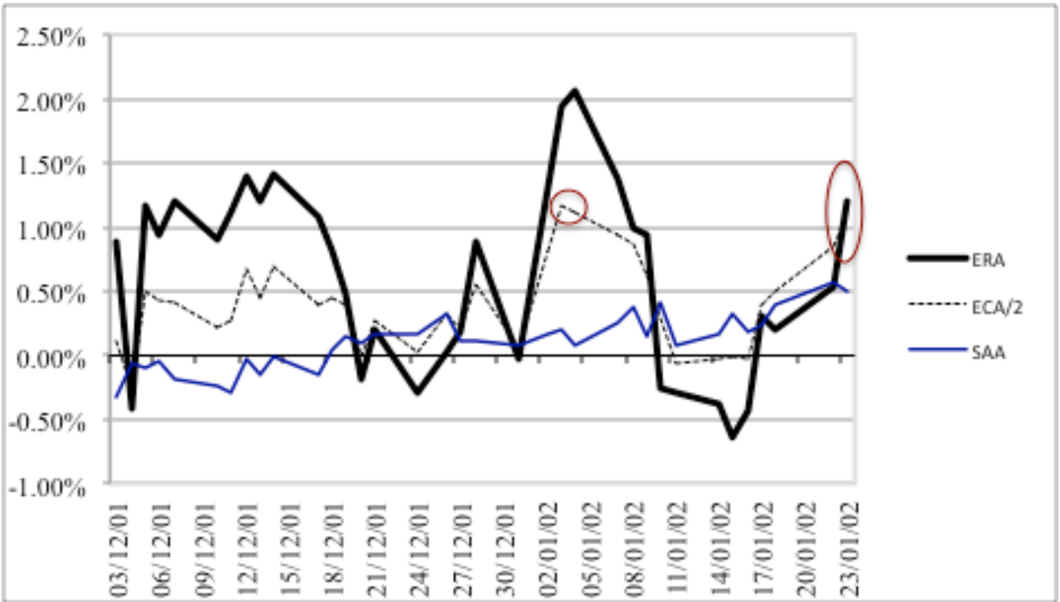



**Figure 3.3.3**: Generation of the entry alarm signal on 23.01.2002 based on the ERA over the ECA/2 metrics.

As marked by ovals in Figure 3.3.3 above, on 23.01.2002, the *ERA* metrics surpasses the recent local maximum of *ECA/2* metrics, observed on 03.01.2002. Such a movement indicates a likely approaching Flight-to-Quality event. As it can be confirmed in the list of the identified in 2002 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.8, the alarm signal, generated on 23.01.2002, is followed by the Flight-to-Quality whose initial date is 24.01.2002.

#### 3.3.1.2. Alarm signals based on *SAA* downside moves

The *SAA* metrics downside move means a decrease in the investors′ demand for safe assets. Such a situation is the opposite of a Flight-to-Quality. Thus, one could expect a Flight-to-Quality to occur after the *SAA* metrics decreases below certain limits. By analogy with the *ERA* upside moves, the *SAA* downside moves do not always generate alarm signals warning of Flight-to-Quality ignitions, rather only a few of them which must be related to specific changes in asset-holding appetite. Thus, only the *SAA* downside moves, which result in the *SAA* values below the values of asset-holding appetites observed in a recent past produce alarm signals. As there are three different asset-holding appetite metrics, which are developed and used in this study, namely *ERA*, *SAA*, and *ECA/2*, the previous historical behavior of each of them can be used for comparison with the *SAA* downside moves. Thus, three different situations causing Flight-to-Quality alarm signals can be distinguished. The first is related to the alarms generated by the *SAA* downside move surpassing its previously observed local minimum. The second situation is the *SAA* downside move surpassing a recently observed local minimum of the *ERA* metrics. Third type of alarm is produced by the *SAA* downside move below the recent local minimum of *ECA/2* metrics. The next exposition explains each of these three conditions in more detail and provides a set of corresponding examples.

***SAA* downside move below its previously observed local minimum**

The *SAA* metrics´ downside move to a level lower than its own recently observed local minimum is considered as an alarm signal warning of an approaching Flight-to-Quality event. This situation can be explained as follows. The *SAA* metrics´ decrease means a lack of interest for safe assets. Thus, one can expect a Flight-to-Quality to occur after *SAA* metrics decreases to its previous minimum.

In the modeled investment universe, as there are only two, safe and risky, asset classes, it becomes easier to comprehend the duality of market behavior. The market participants either believe that the world is on the road to recovery, meaning increase in appetite for risky assets, or the world is not optimistic, which is just the contrary situation, i.e. Flight-to-Quality. Hence, the concept of Flight-to-Quality is linked to the market´s view of the future state of the world economy. Investors either believe that future economic prospects are favorable, in which case their appetite for risky assets grows; or investors consider that future prospects are bad, in which case Flight-to-Quality takes place.

The diminishing interest for safe assets, dropping below its previously observed local minimum, means that the risky appetite should soon slide down in order to provide recovery to the safe assets. The number of potential buyers of safe securities is likely to overcome the number of potential sellers of the safe securities, as it was already observed in the recent past, when at the similar levels of appetite for safe assets a similar Flight-to-Quality process was ignited. The upcoming increase in the *SAA* metrics, resulting from this situation, is likely to be accompanied by the inverse move, representing a drop in the investors´ appetite for risky assets, i.e. Flight-to-Quality.

In order to illustrate a generation of an alarm signal under these circumstances, an interval from 01.09.2010 to 03.11.2010, is chosen. The *SAA* metrics dynamics along with the *ERA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.4 below.

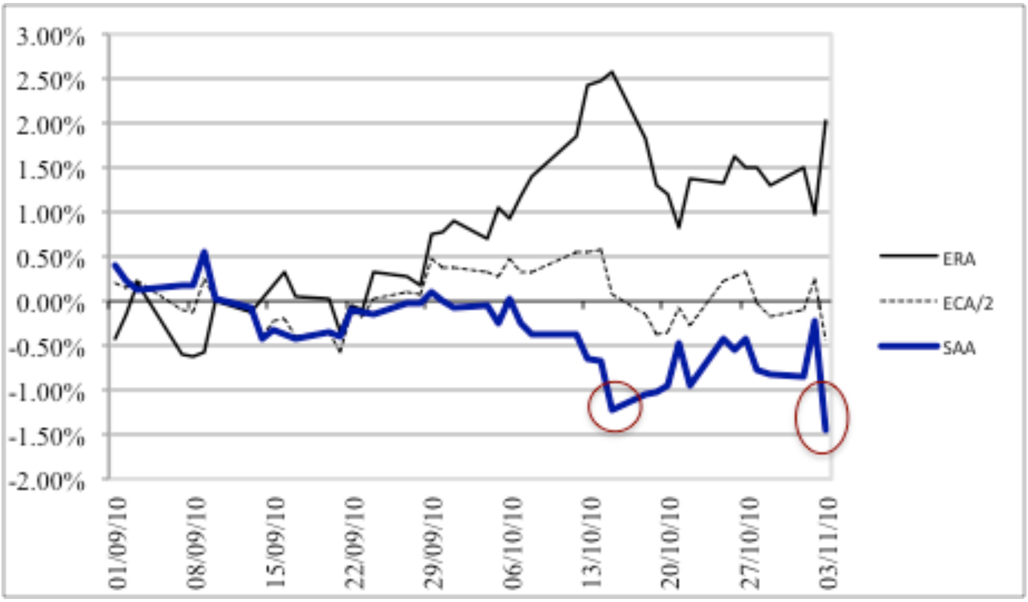



**Figure 3.3.4**: Generation of the entry alarm signal on 03.11.2010 based on the SAA metrics.

As it is marked by ovals in Figure 3.3.4, *SAA* metrics surpasses on 03.11.2010 its previous local minimum, observed on 15.10.2010. Such a movement indicates the likely approach of Flight-to-Quality event. As can be seen in the list of the identified in 2010 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.16, the Flight-to-Quality happens 05.11.2010, two days after the appearance of the described above alarm signal.

***SAA downside move below previously observed local minimum of ERA***

The *SAA* metrics´ downside move below a recently observed local minimum of *ERA* metrics is considered an alarm signal warning of an approaching Flight-to-Quality event. This situation can be explained as follows. The *SAA* metrics´ decreasing trend implies the absence of the investors´ willingness to hold their assets in safe financial instruments. This tendency is likely to be corrected if the appetite for safe assets drops below a previously observed minimum level of the investors´ appetite for risky assets, which represents a certain benchmark of minimal demand for risky assets, but also for safe assets. When the appetite for safe assets reaches this lowest acceptable limit, the likelihood of switching investors´ preferences from risky to safe assets increases.

In order to illustrate an alarm signal generated by the *SAA* metrics downside move below the *ERA* metrics, an interval from 18.03.2003 to 07.05.2003, is chosen. The *SAA* metrics dynamics along with the *ERA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.5.

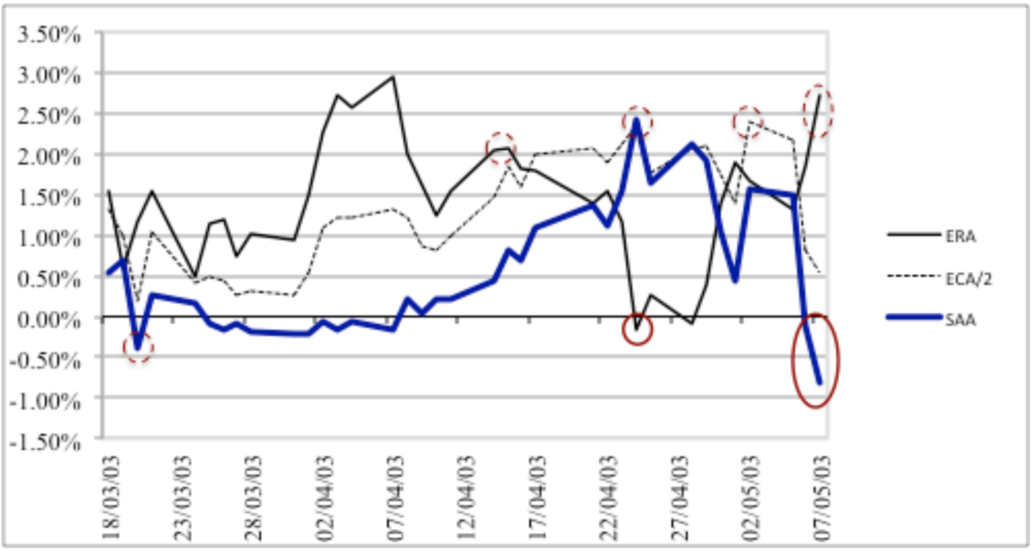



**Figure 3.3.5**: Generation of the alarm signal on 07.05.2003 based on the SAA below the ERA metrics.

As marked by ovals in Figure 3.3.5, on 07.05.2003, the *SAA* metrics surpasses the previous local minimum of *ERA*, observed on 24.04.2003. Such a movement indicates the likely approach of a Flight-to-Quality event. As can be seen in the list of the identified in 2003 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.9, the corresponding Flight-to-Quality happens on 13.05.2003, posterior to the generated on 07.05.2003 alarm signal.

It is worth noting that an alarm, which is generated based on one metrics, could coincide with additional alarm signals, which are generated based on other metrics, the *ERA* and the *SAA* in the considered example. On 07.05.2003 the *ERA* assumes value greater than its previous local maximum on 15.04.2003 and the previous local maxima of the *SAA* and the *ECA/2* on 24.04.2003 and on 02.05.2003, respectively. Additionally, on 07.03.2003 the *SAA* moves below its previous local minimum, observable on 20.03.2003. The additional alarms described above, signaling an approaching Flight-to-Quality, are depicted by the dashed ovals in Figure 3.3.5 above.

***SAA downside move below previously observed local minimum of ECA/2***

The *SAA* metrics downside move below a recently observed local minimum of *ECA/2* metrics is considered an alarm signal warning of an approaching Flight-to-Quality event. This situation can be explained as follows. The *SAA* metrics´ decrease means the deterioration of the investors´ preferences to hold safe assets instead of risky financial instruments. When the appetite for safe assets falls below the previously observed minimum level of the investors´ willingness to invest in both safe and risky financial instruments, such tendency is likely to be inverted, switching investors´ preferences from risky to safe assets, as the low acceptable boundary for assets demand indicated by the recently observed local minimum of *ECA/2* has lost such a status.

In order to illustrate an alarm signal generated by the *SAA* metrics´ downside move below the *ECA/2* metrics, an interval from 11.03.1999 to 07.05.1999, is chosen. The *SAA* metrics dynamics along with the *ERA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.6 below.

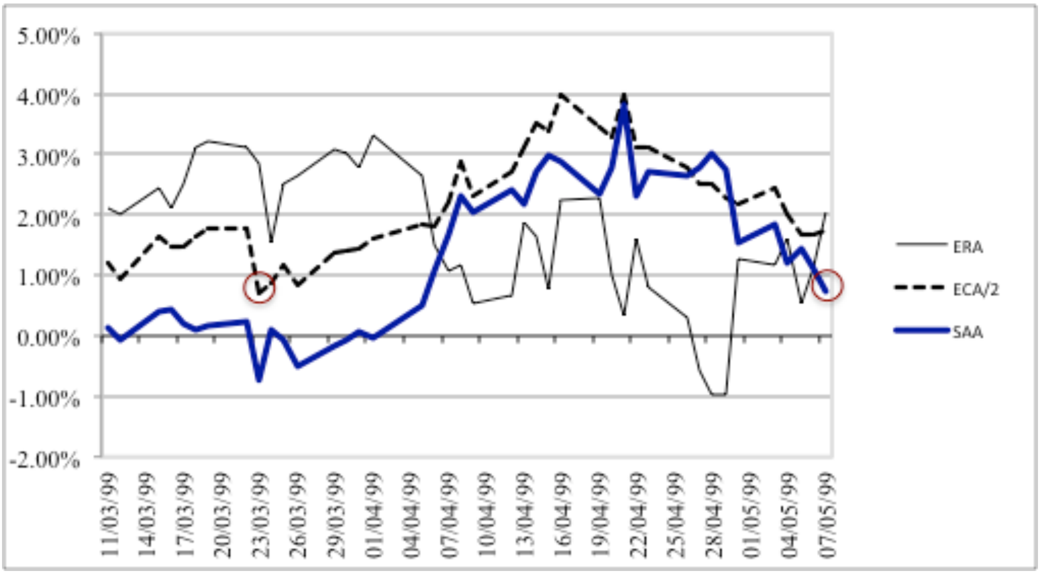



**Figure 3.3.6**: Generation of the entry alarm signal on 07.05.1999 based on the SAA below the ECA/2 metrics.

As marked by ovals in Figure 3.3.6, on 07.05.1999, the *SAA* metrics surpasses the previous local minimum of *ECA/2*, observed on 23.03.1999. Such a movement indicates a likely approaching Flight-to-Quality event. As can be seen in the list of the identified in 1999 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.5, the Flight-to-Quality happens on 07.05.1999, the date of the appearance of the alarm signal described above.

### 3.3.1.3. Alarm signals based on *ECA/2* upside move above its previous local maximum

The *ECA/2* is nothing but the total investors´ appetite of the modeled investment universe divided by 2 in order to be commensurable and, hence, directly comparable with the other developed *ERA* and *SAA* metrics describing the respective investment sub-universes. The *ECA/2* upside move, caused by simultaneous increases in the investors´ appetites for safe and risky assets, means willingness of investors to make investments in financial instruments as opposed to non-financial assets. When the total investors´ appetite reaches its previously observed local maximum while investors´ appetites for both safe and risky assets increase, deterioration in the aggregate asset appetite is likely to occur. This could be ascribed to the fact that the previously prevailed level of the total asset-holding appetite is overpassed. In such circumstances the decrease in the aggregated investors´ appetite is likely be caused by a slide in the appetite for risky assets while preserving and/ or augmenting the appetite for safe assets, which is nothing but Flight-to-Quality. Thus, the *ECA/2* metrics upside move above its previously observed local maximum, accompanied by a simultaneous increase in the *ERA* and *SAA* metrics, is considered an alarm signal warning of an approaching Flight-to-Quality event.

In order to illustrate a generation of an alarm signal based on the *ECA/2* metrics upside move over its previously observed local maximum, an interval from 27.08.1999 to 06.10.1999, is chosen. The *ECA/2* metrics dynamics along with the *ERA* and *SAA* metrics within the selected period are depicted in Figure 3.3.7.

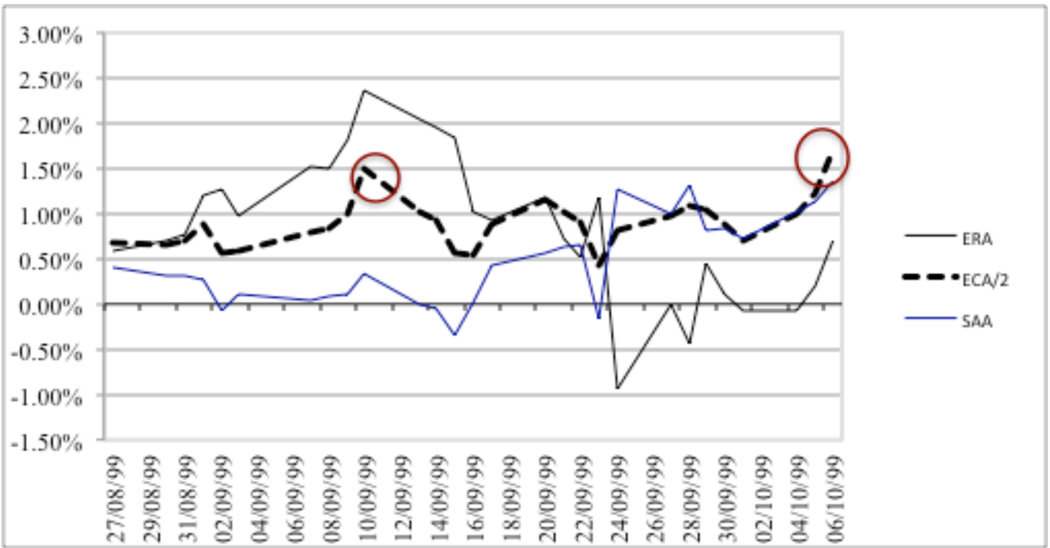



**Figure 3.3.7**: Generation of the entry alarm signal on 06.10.1999 based on ECA/2 metrics.

As marked by ovals in Figure 3.3.7, on 06.10.1999, the *ECA/2* metrics surpasses its previous local maximum, observed on 10.09.1999. Such a movement indicates a likely approaching Flight-to-Quality event. As can be checked in the list of the identified in 1999 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.5, the Flight-to-Quality happens on 08.10.1999, posterior to the appearance of the described above alarm signal generated on 06.10.1999.

## 3.3.2. Generation of Exit Signals warning of Flight-to-Quality termination

The exit alarm signals warning of the approaching end dates of Flights-to-Quality can be separated into the three groups: the *ERA* metrics downside moves, the *SAA* metrics upside moves, and the *ECA/2* metrics downside moves. These groups of exit signals are separately described and illustrated by selected examples on how such warnings are generated.

### 3.3.2.1. Alarm signals based on *ERA* downside moves

Considering the *ERA* downside moves, it is implicit that not all such moves should result in the alarm signaling the termination of Flight-to-Quality, but only a few of them which must be specific in the sense of comparison with the asset-holding appetite. Thus, only the *ERA* downside movements, which reduce the respective risky asset appetite measure below the observed in a recent past asset-holding appetites, result in the alarm signals generation. As there are three proposed metrics allowing quantification of the investors' appetite to hold financial instruments, namely *ERA*, *SAA*, and *ECA/2*, the previously observed historical behavior of each can be used for comparison with the *ERA* downside moves. Thus, three different situations causing Flight-to-Quality termination alarm signals can be distinguished. The first is related to the alarms generated by the *ERA* downside move surpassing its previously observed local minimum. The second situation is the *ERA* downside move below a recently observed local minimum of *SAA* metrics. The third type of alarm is produced by the *ERA* downside move to below a recent local minimum of the *ECA/2* metrics. Further on, each of these three conditions allowing for an appearance of the alarm signals, advising on a near termination of Flight-to-Quality, is discussed in more detail, and the corresponding examples are provided.

***ERA downside move below its previously observed local minimum***

The *ERA* metrics downside move to a level lower than its own recently observed local minimum is considered an alarm signal warning of an approaching termination of a Flight-to-Quality event. This situation can be understood as follows. The local minimum of the *ERA* metrics in a recent past indicates an acceptable level of investors´ unwillingness to invest in risky assets. After this level is reached, the risk appetite in the investment universe is likely to recover. In other words, one would expect the system to reestablish its willingness to hold/ invest in risky assets when deterioration is observed in the risk asset appetites to even lower values than those experienced in a recent past. As any *ERA* local minimum indicates a turning point of risk asset appetite, a new bottom reached by this risk appetite metrics is to be followed by a rather sharp recovery. Such *ERA* metrics dynamics, i.e. the decrease of the risk appetite below its recently observed minimum, is proposed to serve as an alarm for a coming termination of a Flight-to-Quality event.

In order to exemplify the *ERA* metrics downside move dynamics overlapping its previous local minimum as a signal of the approaching termination of the event, an interval from 03.12.2001 to 30.01.2002, is chosen. The *ERA* metrics dynamics along with the behavior of *SAA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.8 below.

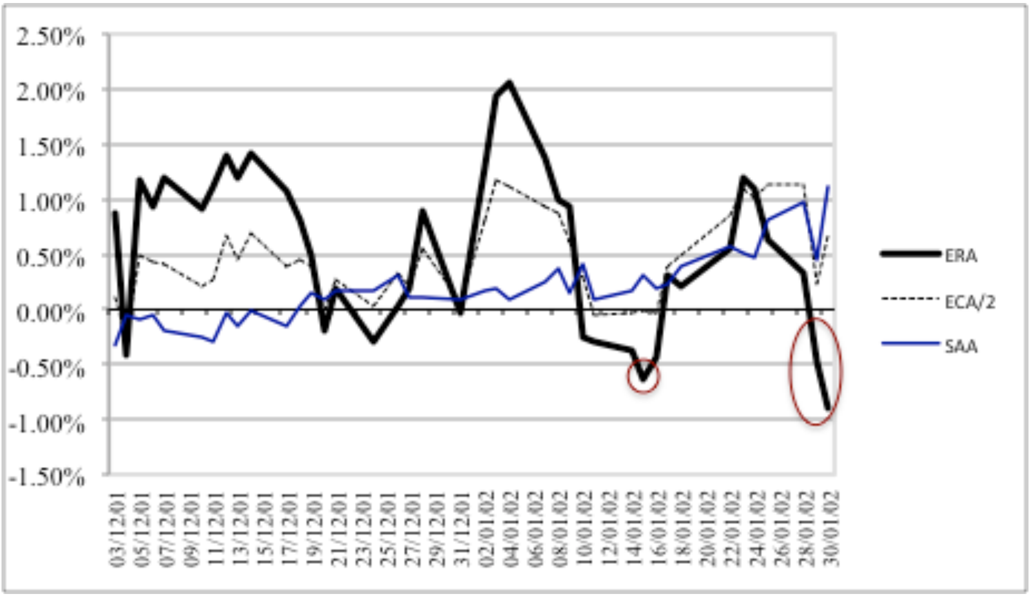



**Figure 3.3.8:** Generation of the exit alarm signal on 30.01.2002 based on the ERA metrics.

As marked by ovals in Figure 3.3.8, on 30.01.2002, the *ERA* metrics moves below its previous local minimum, observable on 15.01.2002. Such a movement indicates the likelihood of an approaching termination of a Flight-to-Quality event. As it can be seen in the list of the identified in 2002 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.8, the Flight-to-Quality terminates on 04.02.2002, posterior to the appearance of the described above exit alarm signal generated on 30.01.2002.

Additionally, it is worth noting that the entry signal generation for the analyzed above Flight-to-Quality 24.01.2002 – 04.02.2002 is illustrated in Figure 3.3.3 in the preceding section 3.3.1.1, which is dedicated to the entry alarm signals based on *ERA* upside moves. This particular entry signal is generated when the *ERA* increases above the previous local maximum of *ECA/2* metrics. As follows from this example, the entry and exit alarms should not be necessarily of the same group of the primary metrics and/or of the same type of the secondary metrics used for comparison.

Some of the considered below exit signals do not correspond to Flights-to-Quality employed as examples in the section 3.3.1 on entry alarm signals. This is made on purpose in order to present the whole range of the possible situations of the exit signals generation. But still to better illustrate the generation of the pair of entry – exit signals, below in the text of the section 3.3.3.1, the Figure 3.3.15 presents the comparison of the historically observed Flight-to-Quality window 23.03.1998 – 03.04.1998 with the corresponding time frame delimited by the entry–exit alarm signals on 19.03.1998 and 03.04.1998, respectively.

***ERA downside move below previously observed local minimum of SAA***

A signal of a termination of a Flight-to-Quality generated by the *ERA* metrics downside move below the recently observed minimum of *SAA* metrics can be explained as follows. The local minimum of the *SAA* metrics is a low limit of investors´ appetite for safe assets in a recently observed past. When the appetite for risky assets, quantified by the *ERA* metrics, passes underneath this local minimum of appetite for safe assets, adjusted to the level of riskiness of the risky assets, the new lowest point reached by the risk appetite metrics is likely to be followed by a consecutive recovery resulting in the termination of the Flight-to-Quality event.

In other words, the *ERA* metrics´ decrease means a drop in the investors´ willingness to hold risky assets. Thus, one can expect a Flight-to-Quality to terminate after the *ERA* metrics decreases below the previous local minimum of the *SAA* metrics. The termination of the Flight-to-Quality is a likely outcome of such situation as the previous minimum in the appetite for the safe assets represents the former level at which the recovery in appetite for the assets, in this case safe assets, occurred. It is worth recalling that the appetite for the safe assets is adjusted to the level of riskiness of risky assets, and, thus, the appetite for the safe and the appetite for the risky assets are made comparable. The consecutive increase in the *ERA* metrics, resulting from this situation, is likely to be accompanied by the inverse move, representing a drop in the investors´ appetite for safe assets, i.e. recovery from the terminated Flight-to-Quality.

In order to illustrate a warning alarm signal generated by the *ERA* metrics downside move below the recent local minimum of the *SAA* metrics, an interval from 18.03.2003 to 20.05.2003, is chosen. The *ERA* metrics dynamics along with the *SAA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.9.

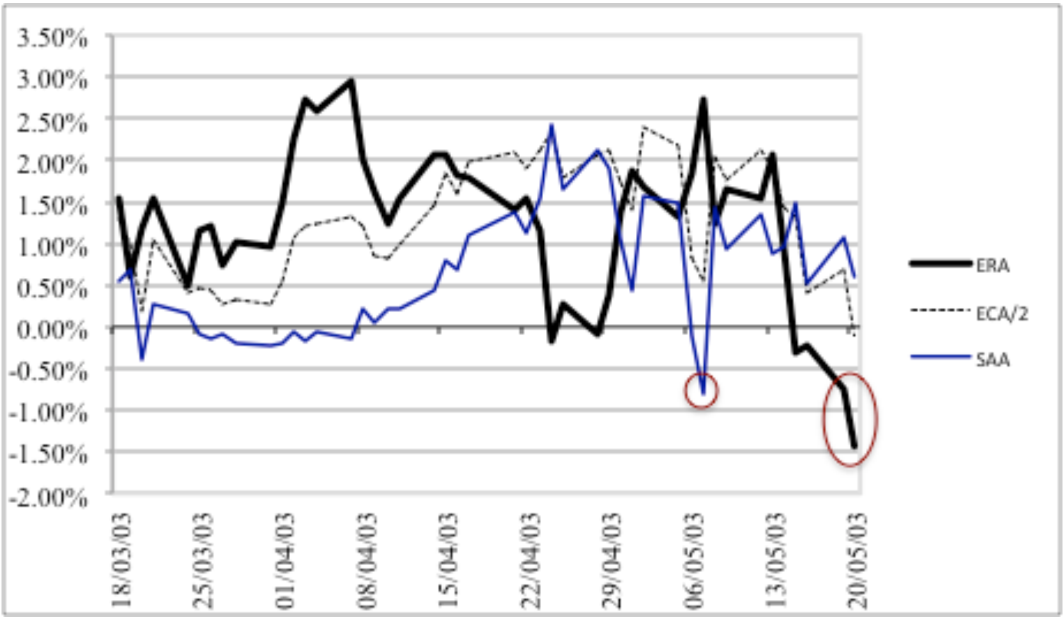



**Figure 3.3.9:** Generation of the exit alarm signal on 20.05.2003 based on the ERA below the SAA metrics.

As marked by ovals in Figure 3.3.9, on 20.05.2003, the *ERA* metrics moves below the *SAA* metrics recent local minimum, observed on 07.05.2003. Such a movement indicates the likelihood of an approaching termination of a Flight-to-Quality event. As it can be seen in the list of the identified in 2003 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.9, the alarm signal, generated on 20.05.2003, indicates the exact end date of the considered here phenomenon.

It is worth noting that the entry signal generation for the analyzed above Flight-to-Quality 13.05.2003 – 20.05.2003 is illustrated in Figure 3.3.5 in the preceding section 3.3.1.2, which is dedicated to the entry alarm signals based on *SAA* downside moves. This particular entry signal is generated when the *SAA* drops below the previous local minimum of *ERA* metrics. As already commented before, the entry and exit alarms should not be necessarily of the same group of the primary metrics and/or of the same type of the secondary metrics used for comparison.

***ERA downside move below previously observed local minimum of ECA/2***

The last type of signal within the class based on the *ERA* downside moves is represented by the *ERA* metrics falling below a recently observed minimum of the *ECA/2* metrics. The sense of this alarm warning of an approaching Flight-to-Quality termination could be comprehended as follows. The *ECA* metrics represents a quantification of the total willingness of the investors´ community to invest in both safe and risky assets. Thus, a drop in the appetite for risky assets (described by *ERA*) below the halved measure of the investors´ unwillingness to hold safe and risky assets (represented by the minimum of the *ECA/2* metrics as risky assets represent a half of the investment universe) can be considered as an indication of a Flight-to-Quality termination. This situation could be thought of as deterioration of a risk appetite below the previously formed and accepted boundary of the absence of the investors´ interest to invest in financial assets, which is likely to lead to the augmentation in risk appetite, ending an occurring Flight-to-Quality.

In order to illustrate an exit alarm signal generated by the *ERA* metrics downside move below the recent local minimum of *ECA/2* metrics, an interval from 20.06.2007 to 16.08.2007, is chosen. The *ERA* metrics dynamics along with the *SAA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.10 below.

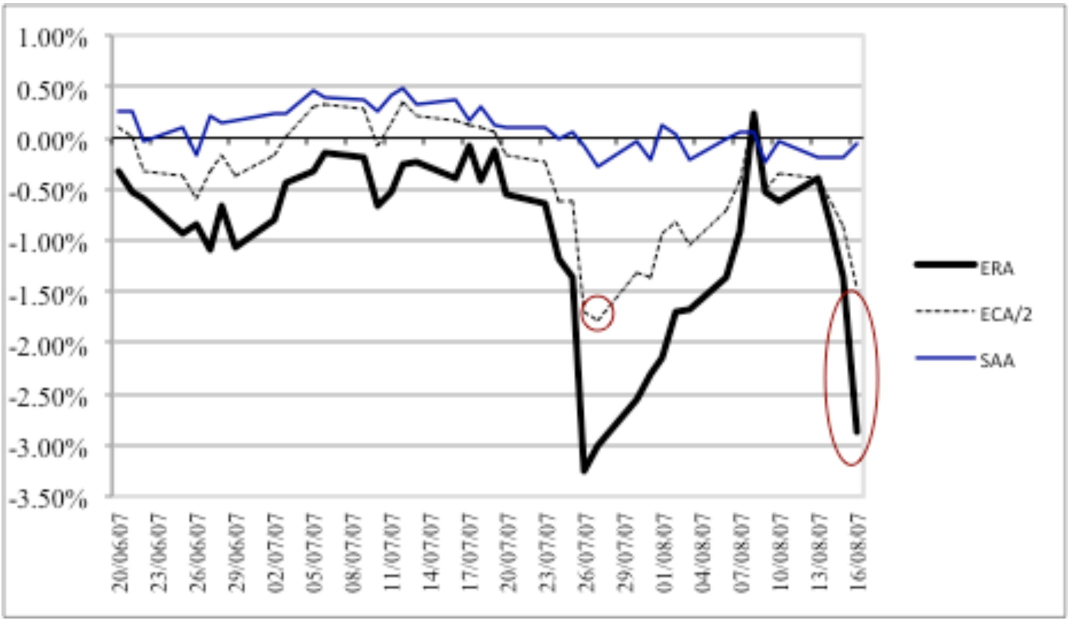



**Figure 3.3.10:** Generation of the exit alarm signal on 16.08.2007 based on the ERA below the ECA/2 metrics.

As marked by ovals in Figure 3.3.10, on 16.08.2007, the *ERA* metrics moves below the recent *ECA/2* local minimum, observed on 27.07.2007. Such a movement indicates the likelihood of an approaching termination of a Flight-to-Quality event. As it can be seen in the list of the identified in 2007 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.13, the alarm signal, generated on 16.08.2007, indicates the exact end date of the phenomenon under consideration.

### 3.3.2.2. Alarm signals based on *SAA* upside moves

The *SAA* metrics' upside move means an increase of the investors´ preferences to hold safe assets, which is the necessary feature of any Flight-to-Quality. Thus, one could expect a Flight-to-Quality to end after the *SAA* metrics has increased above an already occurred, hence acceptable, certain top limit. By analogy with the *ERA* downside moves, the *SAA* upside moves do not always generate alarm signals warning of the weakening and termination of Flight-to-Quality, but only a few of them which must be specific in the sense of asset-holding appetite. Thus, only the *SAA* upside moves which result in the *SAA* values above the observed in a recent past asset-holding appetites produce exit alarm signals. As there are three developed asset-holding appetite metrics, namely *ERA*, *SAA*, and *ECA/2*, the previous historical behavior of each of them can be used for comparison with the *SAA* upside moves. Therefore, three different situations indicating approaching termination of Flight-to-Quality, which can serve as alarm signals, can be distinguished. The first is related to the alarms generated by the *SAA* upside move surpassing up its previously observed local maximum. The second situation is the *SAA* upside move overpassing a recently observed local maximum of the *ERA* metrics. The third type of alarm is produced by the *SAA* upside moves over a recent local maxima of the *ECA/2* metrics. The next exposition explains each of these three conditions in more detail and provides the corresponding examples.

***SAA upside move above its previously observed local maximum***

The *SAA* metrics´ upside move to a level higher than its proper recently observed local maximum is considered an alarm signal warning of an approaching termination of a Flight-to-Quality event. This situation can be explained as follows. The *SAA* metrics´ increase means the boost of investors´ preferences to hold safe assets. Thus, one could expect a termination of a Flight-to-Quality after the *SAA* metrics has increased above its previous maximum, as deterioration in the *SAA* metrics is to be accompanied by an increase in investors´ appetite for risky assets, representing a recovery from Flight-to-Quality.

In order to illustrate a generation of an alarm signal under these circumstances, an interval from 01.10.2008 to 23.10.2008, is chosen. The *SAA* metrics dynamics along with the *ERA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.11.

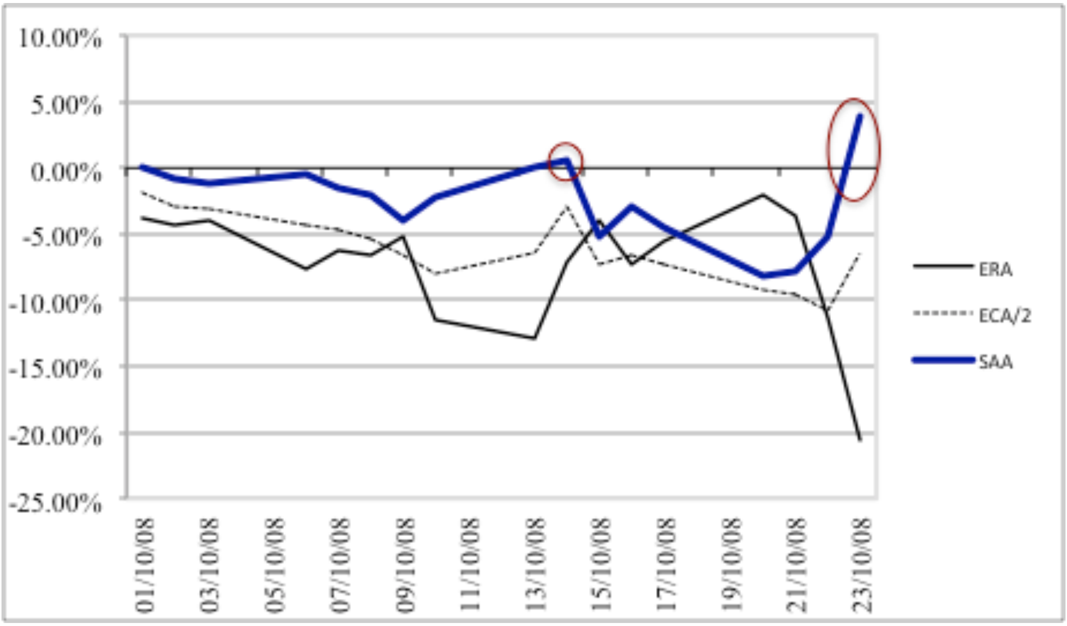



**Figure 3.3.11:** Generation of the exit alarm signal on 23.10.2008 based on the SAA metrics.

As marked by ovals in Figure 3.3.11, on 23.10.2008, the *SAA* metrics surpasses its recent local maximum, observable on 14.10.2008. Such a movement indicates the Flight-to-Quality event to be over. As it can be seen in the list of the identified in 2008 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.14, the alarm signal, generated on 23.10.2008, is followed by the termination of Flight-to-Quality occurring on 24.10.2008.

***SAA upside move above previously observed local maximum of ERA***

The *SAA* metrics upside move above the recently observed local maximum of the *ERA* metrics is considered an alarm signal warning of an approaching Flight-to-Quality event. This situation can be explained as follows. The *SAA* metrics´ increasing values imply a growth of investors´ willingness to hold safe financial instruments. This tendency is likely to change if investors´ appetite for safe assets reaches a level above the previously observed maximum boundary of the investors´ appetite for risky assets, which implicitly stays as the highest acceptable limit of the demand for any assets. When the appetite for safe assets overpasses this highest acceptable magnitude, the likelihood of switching investors´

preferences from safe to risky assets increases, which is nothing but the occurrence opposite of a Flight-to-Quality.

In order to illustrate a generation of an alarm signal caused by the *SAA* metrics upside move above the *ERA* metrics, an interval from 10.03.1998 to 27.05.1998 is chosen. The *SAA* metrics dynamics along with the *ERA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.12.

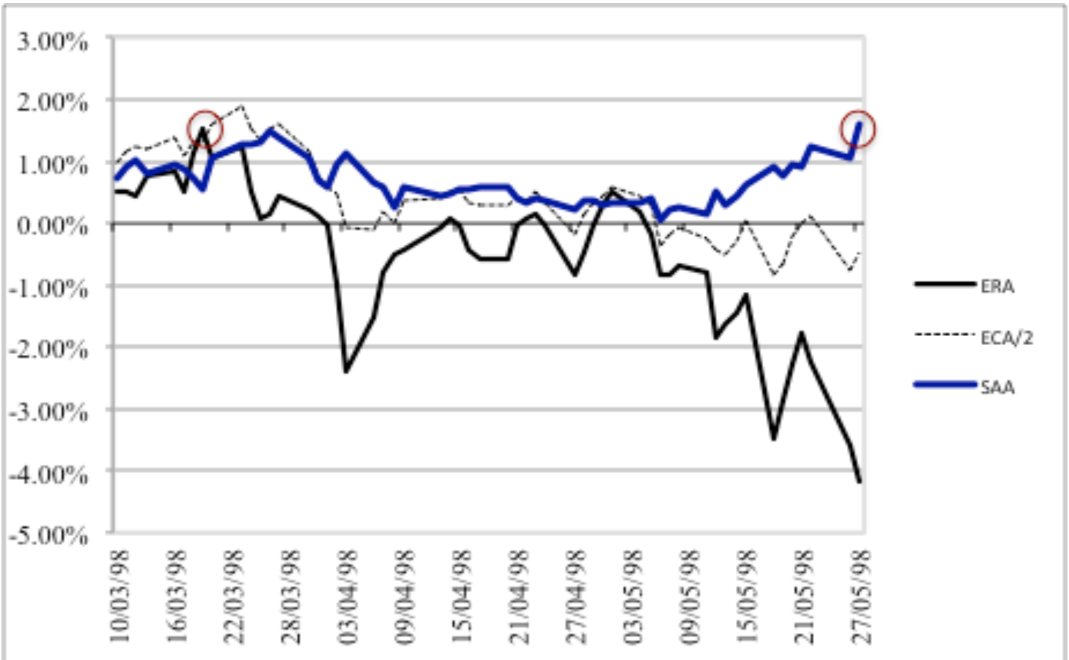



**Figure 3.3.12:** Generation of the exit alarm signal on 27.05.1998 based on the SAA above the ERA metrics.

As marked by ovals in Figure 3.3.12 above, on 27.05.1998, the *SAA* metrics becomes above the local maximum of *ERA*, which had place 19.03.1998. Such a movement indicates the likelihood of an approaching termination of a Flight-to-Quality event. As can be observed in the list of the identified in 1998 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.4, the exit alarm signal, generated on 27.05.1998, matches the termination of the considered Flight-to-Quality.

***SAA upside move above previously observed local maximum of ECA/2***

The *SAA* metrics upside move above a recently observed local maximum of the *ECA/2* metrics is considered an alarm signal warning of an approaching termination of a Flight-to-Quality event. This situation can be explained as follows. The *SAA* metrics´ growth means the increase in the investors´ preferences to hold safe assets instead of risky financial instruments. When the appetite for safe assets exceeds a recently observed maximum level of the investors´ willingness to invest in both safe and risky financial instruments, such tendency is likely to change, switching investors´ preferences from safe to risky assets, as the highest limit of the demand for assets, formed by the recently observed local maximum of *ECA/2*, is overpassed.

In order to illustrate a generation of an alarm signal generated by the *SAA* metrics upside move above the *ECA/2* metrics, an interval from 12.02.2009 to 06.03.2009, is chosen. The *SAA* metrics dynamics along with the *ERA* and *ECA/2* metrics within the selected period are depicted in Figure 3.3.13.

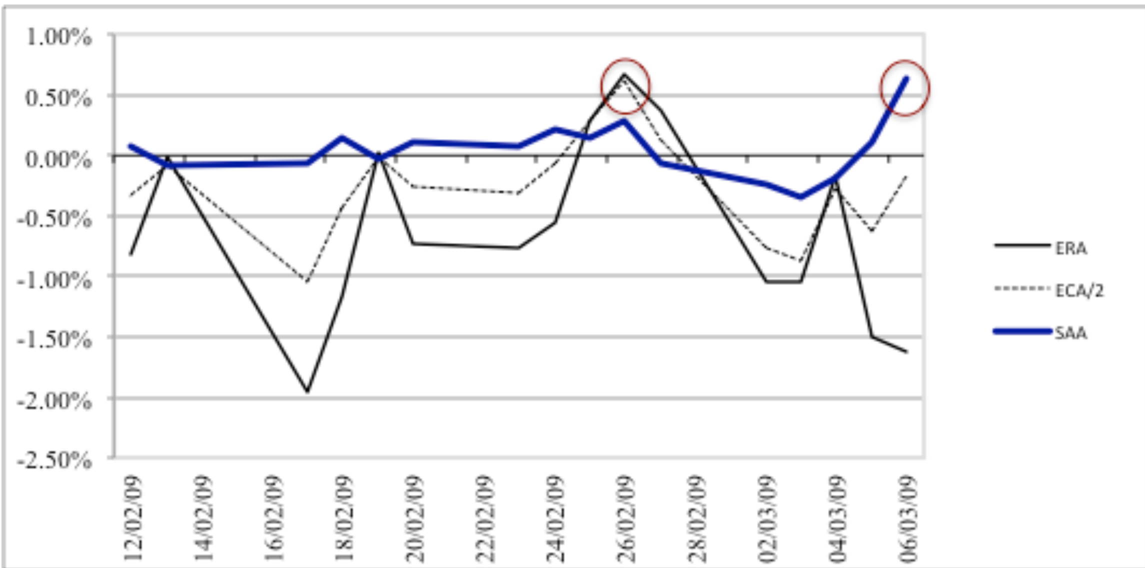



**Figure 3.3.13:** Generation of the exit alarm signal on 06.03.2009 based on the SAA above the ECA/2 metrics.

As marked by ovals in Figure 3.3.13, on 06.03.2009, the *SAA* metrics overpasses the local maximum of *ECA/2*, observed on 26.02.2009. Such a movement indicates the likelihood of a near termination of a Flight-to-Quality event. As can be observed in the list of the identified in 2009 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.15, the exit alarm signal, generated on 06.03.2009, coincides with the corresponding Flight-to-Quality end date.

#### 3.3.2.3. Alarm signals based on ECA/2 downside moves below its previous local minimum

*ECA/2* is nothing but the total investors´ appetite of the modeled investment universe divided by 2 in order to be commensurable and, hence, directly comparable with the *ERA* and *SAA* metrics describing the respective investment sub-universes. The *ECA/2* downside move, caused by simultaneous deterioration in the investors´ appetites for safe and risky assets, can be understood as an unwillingness of investors to make/hold investments in financial instruments, as opposed to non-financial assets. When the total investors´ appetite moves below its previously observed local minimum while investors´ appetites for both safe and risky assets decrease, a coming improvement in the aggregate asset appetite is likely to occur. This could be ascribed to the fact that the prevailed lowest level of the total assets-holding appetite is now higher than the current total assets appetite. In such circumstances an increase in the aggregated investors´ appetite is likely be caused by the growth in the appetite for risky assets while preserving and/ or diminishing the appetite for safe assets, which is nothing but the recovery from Flight-to-Quality. Thus, the *ECA/2* metrics downside move below its previously observed local minimum, accompanied by simultaneous decrease in the *ERA* and *SAA* metrics, is considered as an alarm signal warning of an approaching termination of a Flight-to-Quality event.

In order to illustrate a generation of an alarm signal based on the *ECA/2* metrics downside move below its previously observed local minimum, an interval from 27.08.1999 to 15.10.1999, is chosen. The *ECA/2* metrics dynamics along with the *ERA* and *SAA* metrics within the selected period are depicted in Figure 3.3.14.

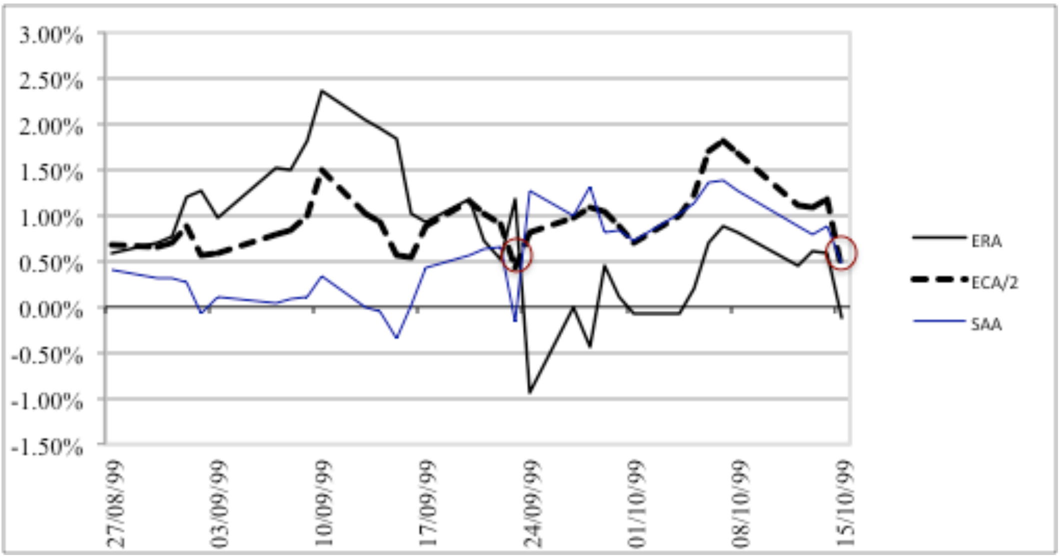



**Figure 3.3.14:** Generation of the exit alarm signal on 15.10.1999 based on the ECA/2 metrics.

As marked by ovals in Figure 3.3.14 above, on 15.10.1999, the *ECA/2* metrics moves below its previous local minimum, observable on 23.09.1999. Such a dynamics indicates the likelihood of an approaching termination of a Flight-to-Quality event. As it can be seen in the list of the identified in 1999 on *ex-post* basis Flights-to-Quality, presented in Table 3.1.5, the exit alarm signal, generated on 15.10.1999, corresponds to the end date of the considered Flight-to-Quality.

It is worth commenting that the entry signal generation for the analyzed above Flight-to-Quality 08.10.1999 – 15.10.1999 is illustrated in Figure 3.3.7 in the preceding section 3.3.1.3, which is dedicated to the entry alarm signals based on *ECA/2* upside moves. This particular entry signal is generated when the *ECA/2* increases above its previous local maximum.

### 3.3.3. Efficiency Analysis of the Alarm Signal System

The efficiency analysis of the proposed Alarm Signal System is divided into two parts, which are followed by the section containing a set of conclusive remarks. Firstly, the general description of the outcomes of the Alarm Signal System applied to the studied period 1998 – 2010 is performed. Secondly, the efficiency of the entry and exit alarms generation is examined both, from the point of view of alarms′ timeliness and from the point of view of comparison of the impacts of the real historically observed Flights-to-Quality and the hypothetical, entry-exit signals delimited, would-be events, which are the "*products*" of the proposed Alarm Signal System.

#### 3.3.3.1. Results of the Alarm Signal System analyses

At this point the generation of the alarm signals is performed along the whole considered historical time interval 1998 – 2010. In this manner, the Alarm Signal System application produces a set of pairs of the entry – exit alarms. Each such a pair of entry – exit alarm signals delimits a time frame of the corresponding would-be, or hypothetical, Flight-to-Quality. It is worth noting that all these alarms, both exit and entry warnings, are generated only with the information available before the event of the respective alarm signal generation. In this sense, one can infer that the alarm signal system delimits hypothetical would-be Flight-to-Quality on *ex-ante*, or before the event, basis.

As it is expected, the time frames of Flights-to-Quality delimited on the before the event basis are not identical to those respective Flight-to-Quality windows while determined using the information available both, before and after the event. The identification of such Flight-to-Quality windows is performed by the total return-based identification algorithm, which is proposed and described in the Part 3.1. As this algorithm employs the data prior and posterior to the identified initial and final dates of Flights-to-Quality, one can say that the time windows of these events are determined on *ex-post* basis.

It is important to assess how different are the time frames and impacts of the would-be events being compared to those of the historically occurred Flights-to-Quality. Thus, as a starting step, the identified on *ex-ante* basis flights out of risky *EMBI* towards safe *ITRROV* indexes within 1998 - 2010 are compared to the historically observed Flights-to-Quality identified on *ex-post* basis within the same period. This comparison is organized year-by-year and presented in Tables 3.3.1 – 3.3.13.

The first two columns on the left of each table of Tables 3.3.1 – 3.3.13 listed below contain the initial and final dates of the occurred Flight-to-Quality as detected by the total return identification technique being applied *a posteriori*. The shadowed cells of the first two columns indicate the initial and final dates of the wrapping or aggregated Flights-to-Quality, which spread over the weaker individual events.

The next two columns present the dates of the entry and exit alarm signals, as produced on *ex-ante* basis by the Alarm Signal System in order to warn of the ignition and the termination of the phenomena, respectively.

Going further to the right, the fifth column indicates the strength of the would-be *ex-ante* Flight-to-Quality, which is delimited by the generated entry and exit alarm signals. This strength is calculated on the date of the appearance of an exit alarm signal as the difference between *ITRROV* and *EMBI* performances calculated in respect to the date marked by the entry alarm. These *ITRROV* and *EMBI* returns are expressed in percentage of the respective index value on the date of the entry alarm signal generation. The annual cumulative strength of the would-be events is given in the bottom line of the fifth column.

The sixth column contains the strength values of the historically observed Flights-to-Quality, as identified on *ex-post* basis. The annual cumulative impact of the events as dated on *ex-post* basis is also presented in the bottom line of the respective column.

Further on the right, the next seventh and eighth columns indicate, respectively, the primary entry metrics, on which the generation of the entry alarm is based, and the metrics describing a prior level of the considered investors′ appetites, to which the move of the primary metrics is compared.

The ninth column contains the *ERA* metrics upside shifts, measured as a difference between the *ERA* value on the date of the appearance of the entry signal and its value on the date of its most pronounced local minimum prior to the entry signal.

The tenth and eleventh columns, respectively, record the primary exit metrics, on which the generation of the exit alarm is based, and the metrics describing a prior level of the considered investors′ appetites, to which the move of the primary metrics is compared.

The twelfth column reveals the *ERA* metrics downside shifts, measured as a difference between the *ERA* value on the date of the appearance of the exit signal and its value on the date of its most pronounced local maximum prior to the exit signal.

In order to exemplify the contents of the Tables 3.3.1 – 3.3.13, the first line of the Table 3.3.1 is selected. The initial date, 23.03.1998, and the final date, 03.04.1998, of the Flight-to-Quality, defined by the application of the total return-based identification technique, are recorded in the first two columns. The strength of this Flight-to-Quality is 2.79%. This value is stored in the sixth column.

The approaching beginning of the event is warned of by the entry signal generated on 19.03.1998, when the *ERA* metrics is increased by 1.44 p.p. (see the ninth column) and is moved over its recent local maximum observed on 04.03.1998, as it is depicted by the solid ovals in Figure 3.3.15 below. The described *ERA* metrics dynamics allowing for the entry signal generation is registered in the seventh, eighth, and ninth columns. The date when the entry signal is generated is written in the third column of the respective Table. Additionally, the *SAA* metrics exhibits a decreasing trend and almost reaches its previous local minimum observed on 04.03.1998.

As to warn of a coming termination of this Flight-to-Quality, the sharp decrease in *ERA* metrics by 3.90 p.p. allows for the appearance of the exit alarm signal on 03.04.1998. The *ERA* metrics becomes below its previous local minimum observed on 20.02.1998 as it is marked by the dashed ovals in Figure 3.3.15. The date when the exit signal is generated is registered in the fourth column of the Table 3.3.1. The described *ERA* metrics behavior is presented in the last three columns of this Table.

The strength of the would-be Flight-to-Quality delimited on *ex-ante* basis applying the proposed Alarm Signal System is 2.30%. This value can be seen in the fifth column of the Table 3.3.1.

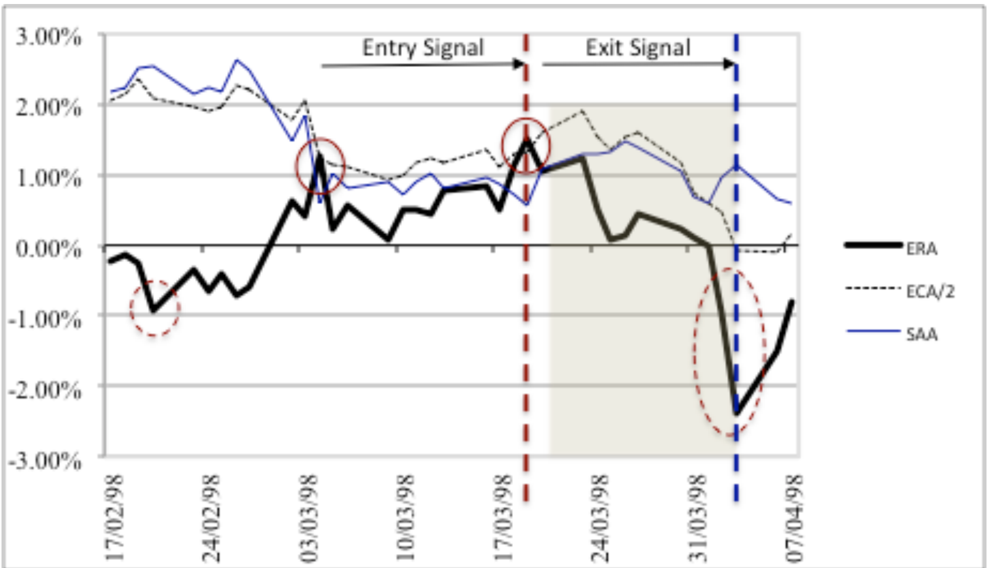



**Figure 3.3.15:** Generation of the entry and exit alarm signals within the period 17.02.1998 – 07.04.1998 to delimit on ex-ante basis the Flight-to-Quality 23.03.1998 – 03.04.1998 (shadowed).

The shadowed time interval in Figure 3.3.15 indicates the historically observed Flight-to-Quality window 23.03.1998 – 03.04.1998. As it can be seen from this Figure, the entry alarm signal appears one working day before the initial date of the event while the exit signal coincides with the end date of the analyzed phenomenon.

Further on the results of the proposed Alarm Signal System applied to the *ITRROV* and *EMBI* indexes are presented.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 23/03/1998 | 03/04/1998 | 19/03/1998 | 03/04/1998 | 2.26% | 2.79% | ERA ↑ | ERA | 1.44% | ERA ↓ | ERA | 3.90% |
| 14/04/1998 | 27/04/1998 | 08/04/1998 | 27/04/1998 | 0.38% | 1.14% | SAA↓ | SAA | 1.88% | ERA ↓ | ERA | 0.98% |
| 01/05/1998 | 18/05/1998 | 01/05/1998 | | ^ | 3.77% | ERA ↑ | ERA | 1.33% | | | |
| 21/05/1998 | 27/05/1998 | | 27/05/1998 | 4.81% | 2.34% | | | | SAA ↑ | ERA | 4.69% |
| 05/06/1998 | 15/06/1998 | 02/06/1998 | | ^ | 4.28% | ERA ↑ | ERA | 2.81% | | | |
| 17/06/1998 | 26/06/1998 | | 26/06/1998 | 5.91% | 4.55% | | | | ERA ↓ | ERA | 3.74% |
| 01/07/1998 | 06/07/1998 | | | | 1.94% | | | | | | |
| 20/07/1998 | 27/07/1998 | 14/07/1998 | | ^ | 3.55% | ERA ↑ | ERA | 6.66% | | | |
| 31/07/1998 | 12/08/1998 | | 10/08/1998 | 11.28% | 11.74% | | | | ERA ↓ | ERA | 14.06% |
| 14/08/1998 | 27/08/1998 | 12/08/1998 | | ^ | 24.24% | SAA↓ | SAA | 0.96% | | | |
| 02/09/1998 | 10/09/1998 | | 10/09/1998 | 25.02% | 9.86% | | | | ERA ↓ | ERA | 6.11% |
| 28/09/1998 | 05/10/1998 | 28/09/1998 | 05/10/1998 | 6.62% | 6.62% | ERA ↑ | ERA | 22.22% | ERA ↓ | ERA | 9.90% |
| 22/10/1998 | 29/10/1998 | 15/10/1998 | 29/10/1998 | -0.10% | 3.44% | ERA ↑ | ERA | 9.81% | ERA ↓ | ERA | 7.72% |
| 06/11/1998 | 12/11/1998 | 06/11/1998 | 12/11/1998 | 3.32% | 3.32% | ERA ↑ | ERA | 3.69% | ERA ↓ | ERA | 6.19% |
| 23/11/1998 | 14/12/1998 | 20/11/1998 | 04/12/1998 | 5.25% | 7.88% | ERA ↑ | ERA | 3.00% | ERA ↓ | SAA | 6.08% |
| Total | | | | 64.75% | 91.46% | | | | | | |

**Table 3.3.1**: Alarm Signals and Flights-to-Quality within 1998.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 06/01/1999 | 14/01/1999 | 05/01/1999 | 14/01/1999 | 12.58% | 12.60% | ERA ↑ | ERA | 7.64% | ERA ↓ | ERA | 12.81% |
| 20/01/1999 | 25/01/1999 | 20/01/1999 | 25/01/1999 | 5.04% | 5.04% | ERA ↑ | ERA | 7.72% | SAA ↑ | SAA | 4.92% |
| 04/02/1999 | 08/02/1999 | | | | 1.50% | | | | | | |
| 16/02/1999 | 03/03/1999 | 12/02/1999 | 25/02/1999 | 0.84% | 2.71% | ERA ↑ | ERA | 10.85% | ERA ↓ | ERA | 4.79% |
| | | 01/04/1999 | 07/04/1999 | -0.13% | | ERA ↑ | ERA | 2.12% | ERA ↓ | ERA | 2.23% |
| 07/05/1999 | 24/05/1999 | 07/05/1999 | 21/05/1999 | 6.36% | 7.68% | SAA ↓ | ECA/2 | 3.00% | ERA ↓ | ERA | 6.83% |
| 22/06/1999 | 28/06/1999 | 16/06/1999 | | ^ | 1.75% | ERA ↑ | ERA | 8.94% | | | |
| 06/07/1999 | 12/07/1999 | | 12/07/1999 | 2.79% | 3.46% | | | | ERA ↓ | ECA/2 | 6.39% |
| 30/07/1999 | 05/08/1999 | 29/07/1999 | 05/08/1999 | 2.13% | 2.32% | ERA ↑ | ECA/2 | 3.06% | ERA ↓ | ERA | 1.78% |
| 17/08/1999 | 20/08/1999 | 17/08/1999 | 20/08/1999 | 1.27% | 1.27% | ERA ↑ | ERA | 2.53% | ERA ↓ | SAA | 1.25% |
| 10/09/1999 | 24/09/1999 | 10/09/1999 | 24/09/1999 | 1.27% | 1.27% | ERA ↑ | ECA/2 | 2.90% | ERA ↓ | ERA | 3.30% |
| 08/10/1999 | 15/10/1999 | 06/10/1999 | 15/10/1999 | 0.91% | 1.26% | ECA/2 ↑ | ECA/2 | 1.63% | ECA/2 ↓ | ECA/2 | 1.00% |
| 26/11/1999 | 01/12/1999 | 24/11/1999 | 01/12/1999 | 0.94% | 1.05% | ERA ↑ | ERA | 2.30% | ERA ↓ | ERA | 1.51% |
| Total | | | | 34.00% | 41.91% | | | | | | |

**Table 3.3.2**: Alarm Signals and Flights-to-Quality within 1999.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 03/01/2000 | 12/01/2000 | 21/12/1999 | 12/01/2000 | -0.21% | 1.45% | ERA ↑ | ERA | 2.64% | ERA ↓ | ERA | 3.39% |
| 24/01/2000 | 31/01/2000 | 24/01/2000 | 27/01/2000 | 0.62% | 1.70% | SAA↓ | SAA | 0.78% | ERA ↓ | ERA | 1.38% |
| 15/02/2000 | 22/02/2000 | 10/02/2000 | 22/02/2000 | 1.01% | 1.42% | ERA ↑ | ERA | 3.54% | ERA ↓ | ERA | 2.01% |
| | | 25/02/2000 | 29/02/2000 | -0.32% | | ERA ↑ | ERA | 2.08% | ERA ↓ | ERA | 0.77% |
| 10/03/2000 | 15/03/2000 | 08/03/2000 | 15/03/2000 | 1.28% | 1.35% | ERA ↑ | ERA | 1.22% | ERA ↓ | ERA | 2.17% |
| 27/03/2000 | 05/04/2000 | 22/03/2000 | 04/04/2000 | 3.83% | 4.27% | ERA ↑ | SAA | 1.43% | ERA ↓ | ERA | 4.42% |
| 12/04/2000 | 17/04/2000 | 12/04/2000 | 17/04/2000 | 1.49% | 1.49% | SAA↓ | SAA | 1.70% | SAA ↑ | SAA | 1.14% |
| 02/05/2000 | 12/05/2000 | 01/05/2000 | 12/05/2000 | 3.82% | 3.97% | ECA/2 ↑ | ECA/2 | 2.48% | ERA ↓ | ERA | 3.16% |
| 18/05/2000 | 22/05/2000 | 18/05/2000 | 22/05/2000 | 2.28% | 2.28% | ERA ↑ | ERA | 2.19% | ERA ↓ | ERA | 2.21% |
| 11/08/2000 | 21/08/2000 | 11/08/2000 | 18/08/2000 | 0.94% | 1.18% | ERA ↑ | ERA | 1.23% | ERA ↓ | ERA | 1.31% |
| 06/09/2000 | 18/09/2000 | 01/09/2000 | 18/09/2000 | 2.27% | 2.72% | ERA ↑ | ERA | 1.53% | ERA ↓ | ERA | 1.90% |
| 04/10/2000 | 26/10/2000 | 03/10/2000 | 17/10/2000 | 4.08% | 5.86% | ERA ↑ | ERA | 2.04% | ERA ↓ | ERA | 4.43% |
| 02/11/2000 | 08/11/2000 | 31/10/2000 | 09/11/2000 | 2.23% | 2.37% | ERA ↑ | ERA | 3.12% | ERA ↓ | ECA/2 | 1.58% |
| 21/11/2000 | 30/11/2000 | 20/11/2000 | 30/11/2000 | 2.31% | 2.35% | ERA ↑ | ERA | 2.42% | ERA ↓ | ERA | 2.53% |
| Total | | | | 25.63% | 32.41% | | | | | | |

**Table 3.3.3**: Alarm Signals and Flights-to-Quality within 2000.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 29/01/2001 | 07/02/2001 | 12/01/2001 | 07/02/2001 | -1.54% | 1.15% | ERA ↑ | ERA | 4.71% | ERA ↓ | SAA | 4.49% |
| 15/02/2001 | 28/02/2001 | 15/02/2001 | 21/02/2001 | 2.54% | 3.18% | ERA ↑ | ERA | 1.98% | ERA ↓ | ERA | 2.38% |
| 09/03/2001 | 23/03/2001 | 07/03/2001 | 19/03/2001 | 3.31% | 5.20% | ERA ↑ | ERA | 2.40% | ERA ↓ | ERA | 2.84% |
| 28/03/2001 | 03/04/2001 | 28/03/2001 | 30/03/2001 | 1.32% | 1.35% | SAA ↓ | SAA | 3.49% | ERA ↓ | ECA/2 | 1.12% |
| 10/04/2001 | 23/04/2001 | 09/04/2001 | 23/04/2001 | 4.48% | 5.59% | ERA ↑ | ERA | 4.84% | ERA ↓ | ERA | 6.29% |
| 24/05/2001 | 01/06/2001 | 24/05/2001 | 01/06/2001 | 1.60% | 1.60% | ERA ↑ | ERA | 1.53% | ERA ↓ | ERA | 3.40% |
| 08/06/2001 | 18/06/2001 | 08/06/2001 | | ^ | 2.61% | ERA ↑ | ERA | 3.66% | | | |
| 26/06/2001 | 12/07/2001 | | 12/07/2001 | 11.32% | 9.87% | | | | ERA ↓ | ERA | 12.04% |
| 23/07/2001 | 01/08/2001 | 26/07/2001 | 01/08/2001 | 1.76% | 3.65% | ERA ↑ | ERA | 8.02% | ERA ↓ | ERA | 1.88% |
| 09/08/2001 | 14/08/2001 | 09/08/2001 | | ^ | 1.01% | ERA ↑ | ERA | 5.84% | | | |
| 16/08/2001 | 21/08/2001 | | 21/08/2001 | 2.95% | 3.40% | | | | ERA ↓ | ERA | 3.53% |
| 04/09/2001 | 14/09/2001 | 04/09/2001 | 14/09/2001 | 6.29% | 6.29% | ERA ↑ | ERA | 3.86% | ERA ↓ | ERA | 5.32% |
| 19/09/2001 | 05/10/2001 | 18/09/2001 | 04/10/2001 | 4.44% | 4.76% | ERA ↑ | ERA | 1.99% | ERA ↓ | ECA/2 | 3.28% |
| 22/10/2001 | 02/11/2001 | 19/10/2001 | 02/11/2001 | 5.74% | 6.21% | ERA ↑ | SAA | 6.15% | ERA ↓ | ECA/2 | 6.16% |
| 15/11/2001 | 19/11/2001 | 15/11/2001 | | ^ | 1.28% | ERA ↑ | ERA | 5.09% | | | |
| 26/11/2001 | 30/11/2001 | | 30/11/2001 | 1.67% | 3.41% | | | | ERA ↓ | ERA | 3.86% |
| 14/12/2001 | 24/12/2001 | 12/12/2001 | 24/12/2001 | 1.19% | 1.45% | ERA ↑ | ERA | 1.80% | ERA ↓ | ERA | 1.69% |
| Total | | | | 47.07% | 62.01% | | | | | | |

**Table 3.3.4**: Alarm Signals and Flights-to-Quality within 2001.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 04/01/2002 | 15/01/2002 | 03/01/2002 | 15/01/2002 | 1.95% | 2.28% | ERA ↑ | ERA | 2.23% | ERA ↓ | ERA | 2.70% |
| 24/01/2002 | 04/02/2002 | 23/01/2002 | 30/01/2002 | 1.36% | 1.66% | ERA ↑ | ECA/2 | 1.84% | ERA ↓ | ERA | 2.10% |
| 12/04/2002 | 10/05/2002 | 12/04/2002 | 30/04/2002 | 1.97% | 3.05% | SAA ↓ | SAA | 0.83% | ERA ↓ | ERA | 2.02% |
| 16/05/2002 | 06/06/2002 | 14/05/2002 | | ^ | 3.94% | ERA ↑ | ERA | 1.20% | | | |
| 10/06/2002 | 21/06/2002 | | 21/06/2002 | 10.09% | 6.40% | | | | ERA ↓ | ERA | 7.39% |
| 28/06/2002 | 30/07/2002 | 28/06/2002 | 29/07/2002 | 6.10% | 7.02% | ERA ↑ | ERA | 5.93% | ERA ↓ | ERA | 5.73% |
| 08/08/2002 | 13/08/2002 | 08/08/2002 | 12/08/2002 | 3.48% | 4.11% | ERA ↑ | ECA/2 | 5.36% | ERA ↓ | ERA | 3.38% |
| 30/08/2002 | 23/09/2002 | 27/08/2002 | 23/09/2002 | 4.44% | 4.56% | ERA ↑ | ERA | 5.77% | ERA ↓ | ERA | 6.22% |
| 25/09/2002 | 30/09/2002 | 25/09/2002 | 27/09/2002 | 1.71% | 1.87% | ERA ↑ | ERA | 1.49% | ECA/2 ↓ | ECA/2 | 1.35% |
| 04/10/2002 | 09/10/2002 | 02/10/2002 | 09/10/2002 | 0.99% | 1.88% | ERA ↑ | ERA | 2.36% | ERA ↓ | ERA | 1.48% |
| 02/12/2002 | 05/12/2002 | 02/12/2002 | 05/12/2002 | 1.43% | 1.43% | ERA ↑ | ERA | 1.62% | ERA ↓ | ERA | 1.68% |
| 23/12/2002 | 30/12/2002 | 18/12/2002 | 30/12/2002 | 0.88% | 1.02% | ERA ↑ | ERA | 1.50% | ERA ↓ | ERA | 1.78% |
| Total | | | | 34.40% | 39.22% | | | | | | |

**Table 3.3.5**: Alarm Signals and Flights-to-Quality within 2002.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 13/01/2003 | 24/01/2003 | 06/01/2003 | 24/01/2003 | 1.57% | 2.51% | ERA ↑ | ERA | 2.36% | ERA ↓ | ERA | 3.34% |
| 13/05/2003 | 20/05/2003 | 07/05/2003 | 20/05/2003 | 1.60% | 3.02% | SAA ↓ | ERA | 2.89% | ERA ↓ | SAA | 4.15% |
| 17/06/2003 | 23/06/2003 | 17/06/2003 | | ^ | 1.99% | ERA ↑ | ERA | 3.52% | | | |
| 25/06/2003 | 07/07/2003 | | 07/07/2003 | 3.13% | 1.69% | | | | ERA ↓ | ERA | 3.87% |
| 21/07/2003 | 06/08/2003 | 21/07/2003 | 06/08/2003 | 2.99% | 2.99% | ERA ↑ | ERA | 3.33% | ERA ↓ | ERA | 3.39% |
| 19/09/2003 | 30/09/2003 | 16/09/2003 | 23/09/2003 | 0.36% | 1.16% | ERA ↑ | ERA | 3.40% | ERA ↓ | ERA | 1.63% |
| 16/10/2003 | 28/10/2003 | 09/10/2003 | 28/10/2003 | 1.33% | 2.22% | ERA ↑ | ERA | 2.28% | ERA ↓ | ERA | 2.63% |
| Total | | | | 10.98% | 15.58% | | | | | | |

**Table 3.3.6**: Alarm Signals and Flights-to-Quality within 2003.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 08/01/2004 | 06/02/2004 | 07/01/2004 | 02/02/2004 | 2.49% | 3.01% | ERA ↑ | ERA | 1.86% | ERA ↓ | ERA | 3.95% |
| 12/02/2004 | 19/02/2004 | | | | 1.11% | | | | | | |
| 13/04/2004 | 21/04/2004 | 06/04/2004 | | ^ | 1.82% | ERA ↑ | ERA | 2.63% | | | |
| 23/04/2004 | 10/05/2004 | | 07/05/2004 | 6.97% | 6.55% | | | | SAA ↑ | SAA | 6.13% |
| 07/06/2004 | 14/06/2004 | 07/06/2004 | 14/06/2004 | 1.15% | 1.15% | ERA ↑ | ERA | 7.66% | ERA ↓ | ERA | 2.37% |
| 12/10/2004 | 25/10/2004 | 05/10/2004 | 20/10/2004 | 0.65% | 1.53% | ERA ↑ | ERA | 1.23% | ERA ↓ | ERA | 1.50% |
| Total | | | | 11.26% | 15.17% | | | | | | |

**Table 3.3.7**: Alarm Signals and Flights-to-Quality within 2004.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 29/12/2004 | 18/01/2005 | 22/12/2004 | 10/01/2005 | 0.82% | 1.38% | ERA ↑ | ERA | 0.99% | ERA ↓ | ERA | 2.03% |
| 08/03/2005 | 15/04/2005 | 07/03/2005 | 24/03/2005 | 3.49% | 4.10% | ERA ↑ | ERA | 2.39% | ERA ↓ | ERA | 3.80% |
| 03/10/2005 | 14/10/2005 | 15/09/2005 | 06/10/2005 | 0.40% | 2.51% | ERA ↑ | ERA | 1.80% | ERA ↓ | ERA | 2.60% |
| Total: | | | | 4.71% | 7.99% | | | | | | |

**Table 3.3.8**: Alarm Signals and Flights-to-Quality within 2005.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 27/02/2006 | 10/04/2006 | 10/02/2006 | 07/03/2006 | 0.35% | 1.80% | ERA ↑ | ERA | 0.96% | ERA ↓ | ERA | 2.00% |
| 03/05/2006 | 24/05/2006 | 28/04/2006 | 15/05/2006 | 1.41% | 2.95% | ERA ↑ | SAA | 1.21% | ERA ↓ | ERA | 1.44% |
| 01/06/2006 | 13/06/2006 | | | | 1.05% | | | | | | |
| 16/06/2006 | 27/06/2006 | 15/06/2006 | 27/06/2006 | 1.40% | 1.47% | ECA/2 ↑ | ECA/2 | 1.96% | ERA ↓ | ERA | 1.27% |
| 05/09/2006 | 22/09/2006 | | | | 1.35% | | | | | | |
| Total: | | | | 3.16% | 8.62% | | | | | | |

**Table 3.3.9**: Alarm Signals and Flights-to-Quality within 2006.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 22/02/2007 | 05/03/2007 | 22/02/2007 | 27/02/2007 | 1.18% | 1.39% | ECA/2 ↑ | ECA/2 | 0.76% | ERA ↓ | ERA | 1.12% |
| 23/05/2007 | 13/06/2007 | 18/05/2007 | 11/06/2007 | 1.25% | 1.53% | ERA ↑ | ERA | 0.80% | ERA ↓ | ERA | 1.45% |
| 18/06/2007 | 29/06/2007 | 19/06/2007 | 29/06/2007 | 1.25% | 1.26% | SAA ↓ | SAA | 0.98% | ERA ↓ | ERA | 0.62% |
| 06/07/2007 | 26/07/2007 | 06/07/2007 | 25/07/2007 | 1.91% | 3.82% | ERA ↑ | ERA | 1.11% | ERA ↓ | ERA | 1.26% |
| 08/08/2007 | 16/08/2007 | 08/08/2007 | 16/08/2007 | 3.73% | 3.73% | ERA ↑ | ERA | 3.50% | ERA ↓ | ECA/2 | 3.10% |
| 04/09/2007 | 10/09/2007 | 04/09/2007 | 10/09/2007 | 1.08% | 1.08% | ERA ↑ | ERA | 3.08% | ERA ↓ | ERA | 0.78% |
| 15/10/2007 | 24/10/2007 | 16/10/2007 | 22/10/2007 | 1.09% | 1.28% | SAA ↓ | SAA | 0.77% | ERA ↓ | ERA | 2.61% |
| 31/10/2007 | 12/11/2007 | 31/10/2007 | | | 2.25% | ERA ↑ | ERA | 1.37% | | | |
| 14/11/2007 | 26/11/2007 | | 26/11/2007 | 4.97% | 3.07% | | | | ERA ↓ | ERA | 4.21% |
| Total: | | | | 16.46% | 19.41% | | | | | | |

**Table 3.3.10**: Alarm Signals and Flights-to-Quality within 2007.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 14/12/2007 | 20/12/2007 | 07/12/2007 | | ^ | 1.02% | ERA ↑ | ERA | 4.22% | | | |
| 26/12/2007 | 04/01/2008 | | | ^ | 1.87% | | | | | | |
| 10/01/2008 | 23/01/2008 | | 22/01/2008 | 3.31% | 2.46% | | | | ERA ↓ | ERA | 4.36% |
| 30/01/2008 | 11/02/2008 | 29/01/2008 | 08/02/2008 | 1.25% | 1.78% | ERA ↑ | ERA | 2.51% | ERA ↓ | ERA | 1.14% |
| 26/02/2008 | 03/03/2008 | 19/02/2008 | | ^ | 1.53% | ERA ↑ | ERA | 1.66% | | | |
| 05/03/2008 | 17/03/2008 | | 14/03/2008 | 2.27% | 2.74% | | | | ERA ↓ | ERA | 2.01% |
| 13/06/2008 | 15/07/2008 | 10/06/2008 | 07/07/2008 | 3.43% | 3.94% | ERA ↑ | ERA | 0.74% | ERA ↓ | ERA | 3.33% |
| 23/07/2008 | 18/08/2008 | 23/07/2008 | 14/08/2008 | 1.03% | 1.30% | ERA ↑ | ERA | 2.72% | ERA ↓ | SAA | 1.74% |
| 29/08/2008 | 17/09/2008 | 29/08/2008 | 17/09/2008 | 8.24% | 8.24% | ERA ↑ | ERA | 0.98% | ERA ↓ | ERA | 7.08% |
| 22/09/2008 | 10/10/2008 | 23/09/2008 | 10/10/2008 | 16.48% | 16.99% | SAA ↓ | SAA | 4.86% | ERA ↓ | ERA | 9.59% |
| 14/10/2008 | 24/10/2008 | 15/10/2008 | 23/10/2008 | 14.24% | 17.25% | ERA ↑ | ERA | 8.79% | SAA ↑ | SAA | 16.52% |
| 04/11/2008 | 20/11/2008 | 03/11/2008 | 20/11/2008 | 7.05% | 9.72% | ERA ↑ | SAA | 24.66% | ERA ↓ | SAA | 13.34% |
| Total: | | | | 57.30% | 68.84% | | | | | | |

**Table 3.3.11**: Alarm Signals and Flights-to-Quality within 2008.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 06/01/2009 | 15/01/2009 | 06/01/2009 | 14/01/2009 | 2.22% | 2.73% | SAA ↓ | SAA | 3.45% | ERA ↓ | ERA | 3.58% |
| 09/02/2009 | 17/02/2009 | 22/01/2009 | 17/02/2009 | 0.98% | 3.53% | SAA ↓ | ECA/2 | 1.76% | ERA ↓ | ECA/2 | 3.81% |
| 26/02/2009 | 06/03/2009 | 25/02/2009 | 06/03/2009 | 1.97% | 2.29% | ERA ↑ | ERA | 2.25% | SAA ↑ | ECA/2 | 2.30% |
| 08/05/2009 | 13/05/2009 | 06/05/2009 | 13/05/2009 | 0.99% | 1.83% | ERA ↑ | ERA | 2.70% | ERA ↓ | ERA | 3.18% |
| 12/06/2009 | 23/06/2009 | 05/06/2009 | 23/06/2009 | 2.48% | 2.88% | ECA/2 ↑ | ECA/2 | 1.05% | ERA ↓ | SAA | 4.11% |
| 01/07/2009 | 08/07/2009 | 01/07/2009 | 08/07/2009 | 1.65% | 1.65% | SAA ↓ | SAA | 1.35% | ERA ↓ | ERA | 1.56% |
| 07/08/2009 | 17/08/2009 | 05/08/2009 | | ^ | 2.20% | ERA ↑ | ERA | 2.01% | | | |
| 21/08/2009 | 02/09/2009 | | 02/09/2009 | 1.91% | 1.24% | | | | ERA ↓ | ECA/2 | 4.07% |
| 16/09/2009 | 28/09/2009 | 16/09/2009 | 28/09/2009 | 1.17% | 1.17% | ERA ↑ | ERA | 4.57% | SAA ↑ | SAA | 4.25% |
| 14/10/2009 | 28/10/2009 | 09/10/2009 | 28/10/2009 | 2.45% | 2.65% | ERA ↑ | ECA/2 | 3.05% | ERA ↓ | ERA | 4.14% |
| 18/11/2009 | 30/11/2009 | 18/11/2009 | 30/11/2009 | 1.47% | 1.47% | ERA ↑ | ERA | 2.22% | ERA ↓ | SAA | 1.58% |
| Total: | | | | 17.29% | 23.64% | | | | | | |

**Table 3.3.12**: Alarm Signals and Flights-to-Quality within 2009.

| Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 11/01/2010 | 05/02/2010 | 21/12/2009 | 05/02/2010 | 1.53% | 3.22% | ERA ↑ | ERA | 0.81% | ERA ↓ | ERA | 3.65% |
| | | 05/03/2009 | 19/03/2009 | -1.44% | | ERA ↑ | ERA | 3.70% | SAA ↑ | ERA | 2.41% |
| 15/04/2010 | 07/05/2010 | 14/04/2010 | 06/05/2010 | 5.12% | 5.47% | ERA ↑ | ERA | 1.53% | ERA ↓ | ERA | 5.59% |
| 13/05/2010 | 25/05/2010 | 11/05/2010 | 25/05/2010 | 3.44% | 4.23% | SAA ↓ | SAA | 2.56% | ERA ↓ | ERA | 2.57% |
| 03/06/2010 | 08/06/2010 | 03/06/2010 | 08/06/2010 | 1.89% | 1.89% | ERA ↑ | ERA | 3.66% | ERA ↓ | ECA/2 | 1.82% |
| 21/06/2010 | 29/06/2010 | 14/06/2010 | 01/07/2010 | 0.44% | 1.44% | ERA ↑ | ERA | 1.98% | SAA ↑ | SAA | 2.43% |
| 09/08/2010 | 16/08/2010 | 03/08/2010 | | ^ | 1.09% | ERA ↑ | ERA | 1.06% | | | |
| 23/08/2010 | 31/08/2010 | | 31/08/2010 | 0.60% | 1.86% | | | | ERA ↓ | ERA | 4.14% |
| 14/10/2010 | 19/10/2010 | 12/10/2010 | 21/10/2010 | 0.35% | 1.04% | ERA ↑ | ECA/2 | 2.22% | ERA ↓ | ERA | 1.76% |
| 05/11/2010 | 16/11/2010 | 03/11/2010 | | ^ | 2.00% | SAA ↓ | SAA | 1.03% | | | |
| 19/11/2010 | 30/11/2010 | | 29/11/2010 | 2.30% | 1.89% | | | | ERA ↓ | SAA | 4.14% |
| 14/12/2010 | 17/12/2010 | 03/12/2010 | 17/12/2010 | 1.10% | 1.66% | ERA ↑ | ERA | 2.42% | ERA ↓ | ERA | 1.57% |
| Total: | | | | 15.33% | 25.79% | | | | | | |

**Table 3.3.13**: Alarm Signals and Flights-to-Quality within 2010.

As it can be seen in Tables 3.3.1 – 3.3.13, analyzing the third and the fourth columns, the entry and exit alarm dates, could eventually correspond to more than one observed Flight-to-Quality. There are 17 such cases, or 17 pairs of the entry-exit alarm signals, which cover 35 historically observed Flights-to-Quality, as identified on *ex-post* basis. For the sake of a better visualization, they are additionally listed all together in Table 3.3.14 below.

| | Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 01/05/1998 | 18/05/1998 | 01/05/1998 | | ^ | 3.77% | ERA ↑ | ERA | 1.33% | | | |
| 2 | 21/05/1998 | 27/05/1998 | | 27/05/1998 | 4.81% | 2.34% | | | | SAA ↑ | ERA | 4.69% |
| 3 | 05/06/1998 | 15/06/1998 | 02/06/1998 | | ^ | 4.28% | ERA ↑ | ERA | 2.81% | | | |
| 4 | 17/06/1998 | 26/06/1998 | | 26/06/1998 | 5.91% | 4.55% | | | | ERA ↓ | ERA | 3.74% |
| 5 | 20/07/1998 | 27/07/1998 | 14/07/1998 | | ^ | 3.55% | ERA ↑ | ERA | 6.66% | | | |
| 6 | 31/07/1998 | 12/08/1998 | | 10/08/1998 | 11.28% | 11.74% | | | | ERA ↓ | ERA | 14.06% |
| 7 | 14/08/1998 | 27/08/1998 | 12/08/1998 | | ^ | 24.25% | SAA↓ | SAA | 0.96% | | | |
| 8 | 02/09/1998 | 10/09/1998 | | 10/09/1998 | 25.02% | 9.86% | | | | ERA ↓ | ERA | 6.11% |
| 9 | 22/06/1999 | 28/06/1999 | 16/06/1999 | | ^ | 1.75% | ERA ↑ | ERA | 8.94% | | | |
| 10 | 06/07/1999 | 12/07/1999 | | 12/07/1999 | 2.79% | 3.46% | | | | ERA ↓ | ECA/2 | 6.39% |
| 11 | 08/06/2001 | 18/06/2001 | 08/06/2001 | | ^ | 2.61% | ERA ↑ | ERA | 3.66% | | | |
| 12 | 26/06/2001 | 12/07/2001 | | 12/07/2001 | 11.32% | 9.87% | | | | ERA ↓ | ERA | 12.04% |
| 13 | 09/08/2001 | 14/08/2001 | 09/08/2001 | | ^ | 1.01% | ERA ↑ | ERA | 5.84% | | | |
| 14 | 16/08/2001 | 21/08/2001 | | 21/08/2001 | 2.95% | 3.40% | | | | ERA ↓ | ERA | 3.53% |
| 15 | 15/11/2001 | 19/11/2001 | 15/11/2001 | | ^ | 1.28% | ERA ↑ | ERA | 5.09% | | | |
| 16 | 26/11/2001 | 30/11/2001 | | 30/11/2001 | 1.67% | 3.41% | | | | ERA ↓ | ERA | 3.86% |
| 17 | 16/05/2002 | 06/06/2002 | 14/05/2002 | | ^ | 3.94% | ERA ↑ | ERA | 1.20% | | | |
| 18 | 10/06/2002 | 21/06/2002 | | 21/06/2002 | 10.09% | 6.40% | | | | ERA ↓ | ERA | 7.39% |
| 19 | 17/06/2003 | 23/06/2003 | 17/06/2003 | | ^ | 1.99% | ERA ↑ | ERA | 3.52% | | | |
| 20 | 25/06/2003 | 07/07/2003 | | 07/07/2003 | 3.13% | 1.69% | | | | ERA ↓ | ERA | 3.87% |
| 21 | 13/04/2004 | 21/04/2004 | 06/04/2004 | | ^ | 1.82% | ERA ↑ | ERA | 2.63% | | | |
| 22 | 23/04/2004 | 10/05/2004 | | 07/05/2004 | 6.97% | 6.55% | | | | SAA ↑ | SAA | 6.13% |
| 23 | 31/10/2007 | 12/11/2007 | 31/10/2007 | | ^ | 2.25% | ERA ↑ | ERA | 1.37% | | | |
| 24 | 14/11/2007 | 26/11/2007 | | 26/11/2007 | 4.97% | 3.07% | | | | ERA ↓ | ERA | 4.21% |
| 25 | 14/12/2007 | 20/12/2007 | 07/12/2007 | | ^ | 1.02% | ERA ↑ | ERA | 4.22% | | | |
| 26 | 26/12/2007 | 04/01/2008 | | | ^ | 1.87% | | | | | | |
| 27 | 10/01/2008 | 23/01/2008 | | 22/01/2008 | 3.31% | 2.46% | | | | ERA ↓ | ERA | 4.36% |
| 28 | 26/02/2008 | 03/03/2008 | 19/02/2008 | | ^ | 1.53% | ERA ↑ | ERA | 1.66% | | | |
| 29 | 05/03/2008 | 17/03/2008 | | 14/03/2008 | 2.27% | 2.74% | | | | ERA ↓ | ERA | 2.01% |
| 30 | 07/08/2009 | 17/08/2009 | 05/08/2009 | | ^ | 2.20% | ERA ↑ | ERA | 2.01% | | | |
| 31 | 21/08/2009 | 02/09/2009 | | 02/09/2009 | 1.91% | 1.24% | | | | ERA ↓ | ECA/2 | 4.07% |
| 32 | 09/08/2010 | 16/08/2010 | 03/08/2010 | | ^ | 1.09% | ERA ↑ | ERA | 1.06% | | | |
| 33 | 23/08/2010 | 31/08/2010 | | 31/08/2010 | 0.60% | 1.86% | | | | ERA ↓ | ERA | 4.14% |
| 34 | 05/11/2010 | 16/11/2010 | 03/11/2010 | | ^ | 2.00% | SAA ↓ | SAA | 1.03% | | | |
| 35 | 19/11/2010 | 30/11/2010 | | 29/11/2010 | 2.30% | 1.89% | | | | ERA ↓ | SAA | 4.14% |
| | Total | | | | 101.30% | 138.74% | | | | | | |

**Table 3.3.14**: 17 pairs of Entry-Exit signals vs. 35 historically observed Flights-to-Quality.

Such cases need a special treatment in order to analyze the efficiency of the proposed Alarm Signal System as no direct comparison seems to be meaningful. So, the aggregation of the 35 discussed above historically observed Flights-to-Quality into the 17 historically observed wrapping events is performed. This aggregation procedure can be performed in two different manners. They are the summation and the aggregated view approaches. Figure 3.3.16 below, considers examples of Flights-to-Quality 22.06.1999 – 28.06.1999 and 06.07.1999 – 12.07.1999 from Table 3.3.14, and illustrates the difference in calculations of the cumulative strength of the historically observed events delimited by the entry and exit alarm signals.

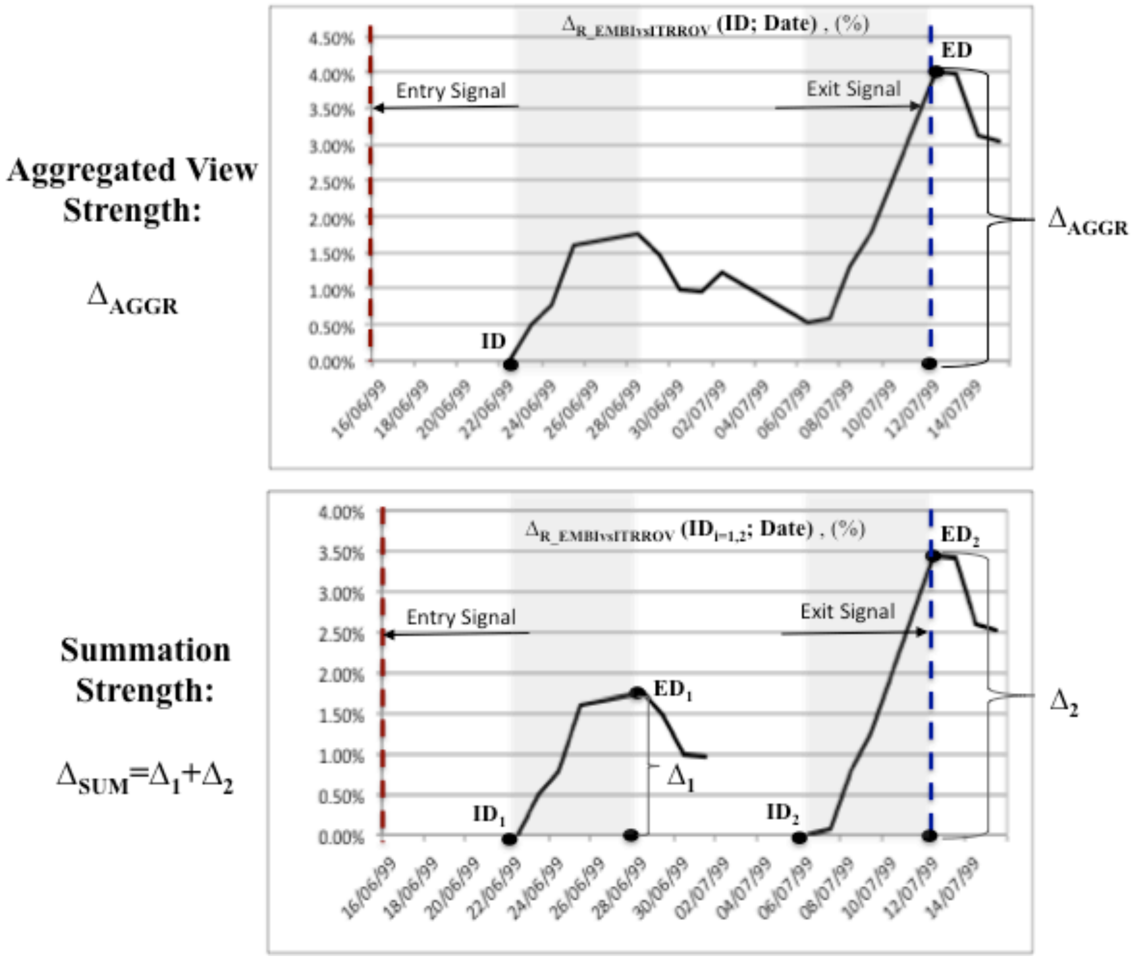



**Figure 3.3.16:** Flight-to-Quality strength calculation: comparison of the Aggregated View and Summation approaches for the alarm signals delimited interval 16.06.1999 – 12.07.1999, covering the Flights-to-Quality 22.06.1999 – 28.06.1999 and 06.07.1999 – 12.07.1999 (shadowed).

The summation approach represents a calculation of a sum of the respective strengths of the individual Flights-to-Quality within the 16 pairs and the 1 group of three events, which are covered by the respective entry-exit alarms in accordance with Table 3.3.14. The result of this procedure is presented in Table 3.3.15 below.

| | Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 01/05/1998 | 27/05/1998 | 01/05/1998 | 27/05/1998 | 4.81% | 6.11% | ERA ↑ | ERA | 1.33% | SAA ↑ | ERA | 4.69% |
| 2 | 05/06/1998 | 26/06/1998 | 02/06/1998 | 26/06/1998 | 5.91% | 8.83% | ERA ↑ | ERA | 2.81% | ERA ↓ | ERA | 3.74% |
| 3 | 20/07/1998 | 12/08/1998 | 14/07/1998 | 10/08/1998 | 11.28% | 15.29% | ERA ↑ | ERA | 6.66% | ERA ↓ | ERA | 14.06% |
| 4 | 14/08/1998 | 10/09/1998 | 12/08/1998 | 10/09/1998 | 25.02% | 34.11% | SAA↓ | SAA | 0.96% | ERA ↓ | ERA | 6.11% |
| 5 | 22/06/1999 | 12/07/1999 | 16/06/1999 | 12/07/1999 | 2.79% | 5.21% | ERA ↑ | ERA | 8.94% | ERA ↓ | ECA/2 | 6.39% |
| 6 | 08/06/2001 | 12/07/2001 | 08/06/2001 | 12/07/2001 | 11.32% | 12.48% | ERA ↑ | ERA | 3.66% | ERA ↓ | ERA | 12.04% |
| 7 | 09/08/2001 | 21/08/2001 | 09/08/2001 | 21/08/2001 | 2.95% | 4.41% | ERA ↑ | ERA | 5.84% | ERA ↓ | ERA | 3.53% |
| 8 | 15/11/2001 | 30/11/2001 | 15/11/2001 | 30/11/2001 | 1.67% | 4.69% | ERA ↑ | ERA | 5.09% | ERA ↓ | ERA | 3.86% |
| 9 | 16/05/2002 | 21/06/2002 | 14/05/2002 | 21/06/2002 | 10.09% | 10.34% | ERA ↑ | ERA | 1.20% | ERA ↓ | ERA | 7.39% |
| 10 | 17/06/2003 | 07/07/2003 | 17/06/2003 | 07/07/2003 | 3.13% | 3.68% | ERA ↑ | ERA | 3.52% | ERA ↓ | ERA | 3.87% |
| 11 | 13/04/2004 | 10/05/2004 | 06/04/2004 | 07/05/2004 | 6.97% | 8.37% | ERA ↑ | ERA | 2.63% | SAA ↑ | SAA | 6.13% |
| 12 | 31/10/2007 | 26/11/2007 | 31/10/2007 | 26/11/2007 | 4.97% | 5.32% | ERA ↑ | ERA | 1.37% | ERA ↓ | ERA | 4.21% |
| 13 | 14/12/2007 | 23/01/2008 | 07/12/2007 | 22/01/2008 | 3.31% | 5.35% | ERA ↑ | ERA | 4.22% | ERA ↓ | ERA | 4.36% |
| 14 | 26/02/2008 | 17/03/2008 | 19/02/2008 | 14/03/2008 | 2.27% | 4.27% | ERA ↑ | ERA | 1.66% | ERA ↓ | ERA | 2.01% |
| 15 | 07/08/2009 | 02/09/2009 | 05/08/2009 | 02/09/2009 | 1.91% | 3.44% | ERA ↑ | ERA | 2.01% | ERA ↓ | ECA/2 | 4.07% |
| 16 | 09/08/2010 | 31/08/2010 | 03/08/2010 | 31/08/2010 | 0.60% | 2.95% | ERA ↑ | ERA | 1.06% | ERA ↓ | ERA | 4.14% |
| 17 | 05/11/2010 | 30/11/2010 | 03/11/2010 | 29/11/2010 | 2.30% | 3.89% | SAA ↓ | SAA | 1.03% | ERA ↓ | SAA | 4.14% |
| | Total | | | | 101.30% | 138.74% | | | | | | |

**Table 3.3.15**: 17 aggregated historically observed Flights-to-Quality by the summation procedure.

On the other hand, the aggregated view approach does not separate the observed period into two or more Flight-to-Quality events and considers the subjacent real event (the aggregated Flight-to-Quality) to start on the initial date of the first Flight-to-Quality and terminate on the end date of the last Flight-to-Quality wrapped by the respective entry-exit signals. The outcome of this procedure is presented in Table 3.3.16 below.

| | Initial Date | End Date | Entry Alarm | Exit Alarm | Ex-Ante Strenth | Observed Strength | Entry Move | Comparative Level | ERA Upside | Exit Move | Comparative Level | ERA Downside |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 01/05/1998 | 27/05/1998 | 01/05/1998 | 27/05/1998 | 4.81% | 4.81% | ERA ↑ | ERA | 1.33% | SAA ↑ | ERA | 4.69% |
| 2 | 05/06/1998 | 26/06/1998 | 02/06/1998 | 26/06/1998 | 5.91% | 6.14% | ERA ↑ | ERA | 2.81% | ERA ↓ | ERA | 3.74% |
| 3 | 20/07/1998 | 12/08/1998 | 14/07/1998 | 10/08/1998 | 11.28% | 14.27% | ERA ↑ | ERA | 6.66% | ERA ↓ | ERA | 14.06% |
| 4 | 14/08/1998 | 10/09/1998 | 12/08/1998 | 10/09/1998 | 25.02% | 28.01% | SAA↓ | SAA | 0.96% | ERA ↓ | ERA | 6.11% |
| 5 | 22/06/1999 | 12/07/1999 | 16/06/1999 | 12/07/1999 | 2.79% | 4.00% | ERA ↑ | ERA | 8.94% | ERA ↓ | ECA/2 | 6.39% |
| 6 | 08/06/2001 | 12/07/2001 | 08/06/2001 | 12/07/2001 | 11.32% | 11.32% | ERA ↑ | ERA | 3.66% | ERA ↓ | ERA | 12.04% |
| 7 | 09/08/2001 | 21/08/2001 | 09/08/2001 | 21/08/2001 | 2.95% | 2.95% | ERA ↑ | ERA | 5.84% | ERA ↓ | ERA | 3.53% |
| 8 | 15/11/2001 | 30/11/2001 | 15/11/2001 | 30/11/2001 | 1.67% | 1.67% | ERA ↑ | ERA | 5.09% | ERA ↓ | ERA | 3.86% |
| 9 | 16/05/2002 | 21/06/2002 | 14/05/2002 | 21/06/2002 | 10.09% | 10.55% | ERA ↑ | ERA | 1.20% | ERA ↓ | ERA | 7.39% |
| 10 | 17/06/2003 | 07/07/2003 | 17/06/2003 | 07/07/2003 | 3.13% | 1.69% | ERA ↑ | ERA | 3.52% | ERA ↓ | ERA | 3.87% |
| 11 | 13/04/2004 | 10/05/2004 | 06/04/2004 | 07/05/2004 | 6.97% | 7.59% | ERA ↑ | ERA | 2.63% | SAA ↑ | SAA | 6.13% |
| 12 | 31/10/2007 | 26/11/2007 | 31/10/2007 | 26/11/2007 | 4.97% | 4.97% | ERA ↑ | ERA | 1.37% | ERA ↓ | ERA | 4.21% |
| 13 | 14/12/2007 | 23/01/2008 | 07/12/2007 | 22/01/2008 | 3.31% | 3.79% | ERA ↑ | ERA | 4.22% | ERA ↓ | ERA | 4.36% |
| 14 | 26/02/2008 | 17/03/2008 | 19/02/2008 | 14/03/2008 | 2.27% | 3.50% | ERA ↑ | ERA | 1.66% | ERA ↓ | ERA | 2.01% |
| 15 | 07/08/2009 | 02/09/2009 | 05/08/2009 | 02/09/2009 | 1.91% | 2.38% | ERA ↑ | ERA | 2.01% | ERA ↓ | ECA/2 | 4.07% |
| 16 | 09/08/2010 | 31/08/2010 | 03/08/2010 | 31/08/2010 | 0.60% | 1.48% | ERA ↑ | ERA | 1.06% | ERA ↓ | ERA | 4.14% |
| 17 | 05/11/2010 | 30/11/2010 | 03/11/2010 | 29/11/2010 | 2.30% | 3.25% | SAA ↓ | SAA | 1.03% | ERA ↓ | SAA | 4.14% |
| | Total | | | | 101.30% | 112.37% | | | | | | |

**Table 3.3.16**: 17 aggregated historically observed Flights-to-Quality based on the aggregated view approach.

As expected the cumulative strength of the historically observed events in the first case is superior to the one in the second case. This is due to the fact that the recoveries of risk appetite between Flights-to-Quality are omitted in the first case and included into consideration in the second.

Further on, the efficiency analysis is performed for the both described above approaches. Note that both of them result in the same 115 Flights-to-Quality regrouped from the 133 events originally observed on *ex-post* basis.

#### 3.3.3.2. Timeliness of Alarm Signals and their Efficiency in Terms of the Delimited Impact

As it is already shown in the section 3.3.3.1, the time frames of Flights-to-Quality delimited on the before the event basis are not identical to those respective Flight-to-Quality windows while determined using the information available both, before and after the event. In other words, the identification of the Flight-to-Quality based on before the event information, or delimiting on *ex-ante* basis, is different from the identification of Flight-to-Quality ignitions and terminations employing all the data available, or the data prior and posterior to the identified initial and final dates of the Flights-to-Quality. The latter procedure can be named as determination of the Flight-to-Quality events on *ex-post* basis.

As it was already mentioned in the previous section 3.3.3.1, it is important to assess how different are the time frames and impacts of the would-be events being compared to those of the historically occurred Flights-to-Quality. Thus, as a continuation of the analyses, the efficiency of the proposed Alarm Signal System is investigated in more detail. Firstly, the accuracy of the alarm signals generation is addressed in terms of the strength of the covered by the entry – exit signals, or would-be Flights-to-Quality compared to the strength of the respective historically observed occurrences. Secondly, the time differences between the generated alarm signals and the ignition/ termination dates are examined.

***Impact Ratio of the would-be Flights-to-Quality to the observed Flights-to-Quality***

The application of the Alarm Signal System to delimiting investment flights out of *EMBI* towards *ITRROV* results in a set of hypothetical Flights-to-Quality identified on *ex-ante* basis with the total cumulative strength of 342.33% as obtained by summation approach. The *ex-post* identified Flights-to-Quality with the event impact parameter (*EIP*) above 1% have the respective total cumulative strength of 452.04% within the same period 1998 – 2010. Thus, the general efficiency/ accuracy of the Alarm Signal System expressed in terms of the impact comparison is 75.73%, see the bottom line of the Table 3.3.17.

The ratio of the would-be Flights-to-Quality to the observed Flights-to-Quality strengths being calculated in accordance with the aggregated view approach is somewhat higher and equals to 80.15%, also see the bottom line of the Table 3.3.17.

The accuracy of the Alarm Signal System is analyzed on a calendar year basis applying both, summation and aggregated view approach. The results are presented in Table 3.3.17.

| Year | Summation Approach | | | | Aggregated View Approach | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Efficiency Ratio | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Efficiency Ratio |
| 1998 | 11 | 64.75% | 91.46% | 70.80% | 11 | 64.75% | 80.36% | 80.57% |
| 1999 | 11 | 34.00% | 41.91% | 81.13% | 11 | 34.00% | 40.70% | 83.54% |
| 2000 | 13 | 25.62% | 32.40% | 79.07% | 13 | 25.62% | 32.40% | 79.07% |
| 2001 | 14 | 47.07% | 62.01% | 75.91% | 14 | 47.07% | 56.37% | 83.50% |
| 2002 | 11 | 34.40% | 39.22% | 87.71% | 11 | 34.40% | 39.43% | 87.24% |
| 2003 | 6 | 10.98% | 15.58% | 70.47% | 6 | 10.98% | 15.03% | 73.05% |
| 2004 | 5 | 11.26% | 15.17% | 74.23% | 5 | 11.26% | 15.77% | 71.40% |
| 2005 | 3 | 4.71% | 7.99% | 58.95% | 3 | 4.71% | 6.61% | 71.26% |
| 2006 | 5 | 3.16% | 8.62% | 36.66% | 5 | 3.16% | 8.62% | 36.66% |
| 2007 | 7 | 16.46% | 19.41% | 84.80% | 7 | 16.46% | 22.85% | 72.04% |
| 2008 | 10 | 57.30% | 68.84% | 83.24% | 10 | 57.30% | 62.72% | 91.36% |
| 2009 | 10 | 17.29% | 23.64% | 73.14% | 10 | 17.29% | 22.58% | 76.57% |
| 2010 | 9 | 15.33% | 25.79% | 59.44% | 9 | 15.33% | 23.68% | 64.74% |
| **Total** | 115 | 342.33% | 452.04% | 75.73% | 115 | 342.33% | 427.12% | 80.15% |

**Table 3.3.17**: Efficiency analysis of the Alarm Signal System on a calendar year basis within 1998 - 2010 for the summation and aggregated view approaches.

As Table 3.3.17 above shows, the years with a high frequency of the Flight-to-Quality events are characterized by a higher value of annual efficiency ratio. Thus, one can conclude, that Alarm Signal System is more efficient in periods of economic distress, which are usually accompanied by the Flight-to-Quality occurrences. In other words, during the years of economic expansion 2005 and 2006, the observed cumulative strength of these relatively rare Flight-to-Quality events is rather modest while compared to other years. Thus, the relatively low levels of efficiency ratios are, to some extend, compensated by their relative unimportance.

Additionally, Table 3.3.18 compares the efficiency ratios as a function of event impact parameter (*EIP*) (*EIP* ≥ 1%, *EIP* ≥ 2%, and *EIP* ≥ 3%) for the two different approaches used to assess the accuracy of the Alarm Signal System along the whole studied time interval 1998 – 2010.

| | Summation Approach | | | | Aggregated View Approach | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio** |
| EIP ≥ 1% | 115 | 342.33% | 452.04% | **75.73%** | 115 | 342.33% | 427.12% | **80.15%** |
| EIP ≥ 2% | 69 | 303.51% | 386.86% | **78.45%** | 67 | 301.24% | 358.78% | **83.96%** |
| EIP ≥ 3% | 51 | 269.78% | 340.36% | **79.26%** | 48 | 263.25% | 309.90% | **84.95%** |

**Table 3.3.18**: Efficiency analysis of the Alarm Signal System for different thresholds of event impact parameter (*EIP*) and for different approaches applied.

As it can be seen from the Table above, the efficiency ratio grows with the strength of the events. This means that the proposed Alarm Signal System is more efficient while delimiting on *ex-ante* basis the stronger events, in a sense of a more accurate coverage of the time intervals with the more pronounced Flight-to-Quality characteristics.

It is worth noting that even for the totality of 115 considered Flights-to-Quality the efficiency ratio in either of approaches is above 75%, indicating a fair accuracy of the

Alarm Signal System as delimiting more than three fourth of the total *ex-post* impact while being applied on *ex-ante* basis.

***Efficiency Ratio dependence on the Risk-Free Interest Rate Dynamics***

As Flights-to-Quality are considered here to be a short-run events, it is worth analyzing their dependence on the short-run moves of the risk-free interest rate described by the *USGG5YR* index. The first step in such analysis is to define the way to assess the interest rate dynamics. With this purpose the 20-day moving average of the *USGG5YR* is calculated. Then the 20-day change in the 20-day moving average of *USGG5YR* is computed. The sense of the considered 20-day change is a measure of a short-term gradient of the risk-free interest rate.

Table 3.3.19 represents the outcome of the efficiency analysis as a function of the risk-free interest rate (*USGG5YR*) for the two proposed (summation and aggregated view) approaches.

| | Summation Approach | | | | Aggregated View Approach | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio** |
| General case | 115 | 342.37% | 452.05% | **75.74%** | 115 | 342.37% | 427.12% | **80.16%** |
| IR decreasing | 68 | 240.69% | 313.72% | **76.72%** | 68 | 240.69% | 295.50% | **81.45%** |
| IR increasing | 47 | 101.68% | 138.33% | **73.51%** | 47 | 101.68% | 131.62% | **77.25%** |

**Table 3.3.19**: Efficiency analysis of the Alarm Signal System as a function of the risk-free interest rate short-run dynamics.

Table above evidences that the efficiency of the Alarm Signal System is higher for the short-run decreases of risk-free interest rate in both approaches. This is an important result as historically the majority of the Flights-to-Quality happen when risk-free interest rate decreases, thus allowing for better delimiting of the majority of events applying the Alarm Signal System.

Further on, the values of risk-free interest rate gradient are assessed and followed by the study of the efficiency dependence on the amplitude of the interest rate changes. The highest rate (increase in *USGG5YR*) is found to be 0.52 p.p. per month while the lowest rate (decrease in *USGG5YR*) equals to -0.62 p.p. per month over the 1998-2010. The results of this analysis are presented in Table 3.3.20.

| Monthly Gradient of USGG5YR Monthly Moving Average | Summation Approach | | | | Aggregated View Approach | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Efficiency Ratio | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Efficiency Ratio |
| [-0.62%; -0.31%[ | 16 | 36.55% | 52.41% | **69.74%** | 16 | 36.55% | 49.53% | **73.79%** |
| [-0.31%; 0%[ | 52 | 204.14% | 261.31% | **78.12%** | 52 | 204.14% | 245.97% | **82.99%** |
| [0%; 0.26%[ | 33 | 76.47% | 104.90% | **72.90%** | 33 | 76.47% | 99.40% | **76.93%** |
| [0.26%; 0.52%] | 14 | 25.21% | 33.43% | **75.41%** | 14 | 25.21% | 32.22% | **78.24%** |

**Table 3.3.20**: Efficiency analysis of the Alarm Signal System as a function of the monthly gradient of the risk-free interest rate.

The lowest range of the risk-free interest rate gradient values ([-0.62%; -0.31%[) could be ascribed to the already developing crisis situations, characterized by unexpected and unprecedented market moves that make the prediction of any events including Flights-to-Quality a harder task. That is why it is comprehensible that this range of the gradient is characterized by a relatively low efficiency ratio (although quite fair, being about 70%).

The slightly negative gradient range of risk-free interest rate ([-0.31%; 0%[) could be comprehended as periods of the initial economic contraction out of which the majority of Flights-to-Quality, including those igniting crises, originates. The Alarm Signal System presents the highest efficiency ratio for this range of the strongest cumulative impact, vindicating its applicability to delimiting on *ex-ante* basis Flight-to-Quality occurrences, which are especially important in a sense of reinforcing financial stability.

The slightly positive gradient range of risk-free interest rate ([0%; 0.26%[) could be attributed to the initial phases of economic expansion. The efficiency ratio of the Alarm Signal System seems to be in line with this conjuncture.

The highest range of the risk-free interest rate gradient values ([0.26%; 0.52%]) could be ascribed to the moments of a rather exuberant growth being a kind of euphoric investors΄ attitudes. Such episodes usually are to be followed by the pronounced drops in risk appetite, which is nothing but Flights-to-Quality. The efficiency ratio, higher than of the previous gradient range, is comprehensible in a light of the exposed arguments and certifies that the Alarm Signal Systems efficiently delimits on *ex-ante* basis the Flight-to-Quality events, which are fruits of financial euphoria. In other words, it is easier to foresee Flights-to-Quality within the periods of euphoric growth than within the periods of a moderate one.

***Efficiency Ratio dependence on the Interest Rate Dynamics and the strength of the event***

In order to assess the efficiency of the Alarm Signal System and verify its applicability to delimiting Flight-to-Quality events of different strength under different interest rate environments, the efficiency ratio is calculated as a function of an increase/ decrease of the interest rate (*USGG5YR*) for diverse ranges of the Flight-t-Quality strength. The results of this analysis are presented in Table 3.3.21.

| | Summation Approach | | | | Aggregated View Approach | | | |
|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio** |
| **IR decreasing** | | | | | | | | |
| EIP ≥ 1% | 68 | 240.69% | 313.72% | **76.72%** | 68 | 240.69% | 295.50% | **81.45%** |
| EIP ≥ 2% | 47 | 223.32% | 283.74% | **78.71%** | 45 | 221.05% | 262.37% | **84.25%** |
| EIP ≥ 3% | 37 | 205.81% | 258.41% | **79.64%** | 34 | 199.28% | 234.66% | **84.92%** |
| **IR increasing** | | | | | | | | |
| EIP ≥ 1% | 47 | 103.57% | 138.33% | **74.87%** | 47 | 103.57% | 131.62% | **78.69%** |
| EIP ≥ 2% | 22 | 80.19% | 103.12% | **77.76%** | 22 | 80.19% | 96.41% | **83.18%** |
| EIP ≥ 3% | 14 | 63.97% | 81.95% | **78.06%** | 14 | 63.97% | 75.24% | **85.02%** |

**Table 3.3.21**: Efficiency analysis of the Alarm Signal System as a function of the monthly gradient of the risk-free interest rate and event impact parameter (EIP).

As it could be seen from the Table above, the efficiency ratio increases monotonically with the increase of the event impact parameter (*EIP*) for both, decreasing and increasing trends of the risk-free interest rate for the two applied approaches. This shows that the Alarm Signal System fairly describes circumstances of the Flight-to-Quality occurrences under decrease and increase of the risk-free interest rate. Nevertheless it is worth noting that, on average, the proposed Alarm Signal System works more efficiently for the phases of the short-run deterioration in economic conditions.

***Efficiency Ratio dependence on the strength of the ERA upside move***

As the *ERA* metrics quantifies the investors´ appetite to hold risky assets, it is worth investigating how the efficiency ratio of the proposed Alarm Signal System varies with the strength of the *ERA* upside move. This study covers all the Flights-to-Quality entry alarms, independently on which metrics they were generated. The *ERA* metrics upside move is measured as a difference between the *ERA* value on the date of the appearance of the entry signal and its value on the date of its most pronounced local minimum prior to the entry signal. The results of this analysis are presented in Table 3.3.22 below.

| ERA Upside Value | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | Efficiency Ratio | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | Efficiency Ratio |
| ]0%; 1%] | 12 | 46.75% | 62.90% | 5.24% | **74.32%** | 12 | 46.75% | 56.80% | 4.73% | **82.31%** |
| ]1%; 2%] | 33 | 72.51% | 96.30% | 2.92% | **75.30%** | 33 | 72.51% | 91.98% | 2.79% | **78.83%** |
| ]2%; 3%] | 28 | 67.55% | 92.51% | 3.30% | **73.02%** | 28 | 67.55% | 87.98% | 3.14% | **76.78%** |
| ]3%; 4%] | 15 | 44.03% | 49.46% | 3.30% | **89.02%** | 15 | 44.03% | 47.75% | 3.18% | **92.21%** |
| ]4%; ∞[ | 22 | 111.53% | 143.93% | 6.54% | **77.49%** | 22 | 111.53% | 135.66% | 6.17% | **82.21%** |

**Table 3.3.22**: Efficiency analysis of the Alarm Signal System as a function of the ERA metrics upside move.

As it can be concluded from Table 3.3.22 above, the average efficiency ratio, calculated over the two last lines is superior to the average efficiency ratio of the three upper lines. This could be considered as an intuitive outcome, due to the fact that the higher the upside in the risk appetite, the most probable is its consecutive slide, i.e. Flight-to-Quality. The fact that the last line represents a decline in efficiency, while compared to the fourth line, could be possibly comprehended through the following consideration. The greatest upside in the risk asset appetite in this case could be not of a pure *EM*-related risk nature and influenced by the factors, which are not considered in our model investment universe.

***Efficiency Ratio dependence on the strength of the ERA upside move and the Interest Rate***

In order to search for a deeper comprehension of conditions leading to major Flights-to-Quality, the efficiency ratio dependence is investigated as a function of both, the strength of the *ERA* upside move and the risk-free interest rate dynamics. The results of this analysis are summarized in Table 3.3.23 below.

| ERA Upside Value/ Interest Rate | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | Efficiency Ratio | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | Efficiency Ratio |
| **IR decreasing** | | | | | | | | | | |
| ]0%; 1%] | 3 | 34.79% | 45.57% | 15.19% | **76.34%** | 3 | 34.79% | 39.49% | 13.16% | **88.10%** |
| ]1%; 2%] | 19 | 41.10% | 57.32% | 3.02% | **71.70%** | 19 | 41.10% | 54.65% | 2.88% | **75.21%** |
| ]2%; 3%] | 14 | 33.30% | 45.20% | 3.23% | **73.67%** | 14 | 33.30% | 43.36% | 3.10% | **76.80%** |
| ]3%; 4%] | 11 | 29.79% | 31.41% | 2.86% | **94.84%** | 11 | 29.79% | 30.86% | 2.81% | **96.53%** |
| ]4%; ∞[ | 18 | 101.71% | 129.82% | 7.21% | **78.35%** | 18 | 101.71% | 122.76% | 6.82% | **82.85%** |
| **IR increasing** | | | | | | | | | | |
| ]0%; 1%] | 9 | 11.96% | 17.33% | 1.93% | **69.01%** | 9 | 11.96% | 17.33% | 1.93% | **69.01%** |
| ]1%; 2%] | 14 | 31.41% | 38.98% | 2.78% | **80.58%** | 14 | 31.41% | 37.33% | 2.67% | **84.14%** |
| ]2%; 3%] | 14 | 34.25% | 47.31% | 3.38% | **72.39%** | 14 | 34.25% | 44.62% | 3.19% | **76.76%** |
| ]3%; 4%] | 4 | 14.24% | 18.05% | 4.51% | **78.89%** | 4 | 14.24% | 16.89% | 4.22% | **84.31%** |
| ]4%; ∞[ | 4 | 9.82% | 14.11% | 3.53% | **69.60%** | 4 | 9.82% | 12.90% | 3.23% | **76.12%** |

**Table 3.3.23**: Efficiency analysis of the Alarm Signal System as a function of the ERA metrics upside move and the risk-free interest rate dynamics.

It is worth noting that for the time intervals, characterized by the decreasing interest rate, which could be ascribed to the economic contraction phases, the most impactful Flights-to-Quality happen for the weakest (] 0%; 1%]) and for the strongest (] 4%; ∞[) *ERA* upsides. These two intervals include episodes around major events, such as, for example, Russian

Default on August 13, 1998 and Lehman Brothers bankruptcy on September 15, 2008. Thus, Flights-to-Quality originated under such conditions make part of major crises within the sample. As such extreme events, they are hard to be precisely delimited on *ex-ante* basis. That is why, for the same reasons that exposed below Table 3.3.22, the highest efficiency ratio is observed for (] 3%; 4%] *ERA* upside intervals.

On the other hand, for the periods, characterized by the increasing interest rate (see Table 3.3.23), which could be ascribed to the economic expansion phases, on average, the Flights-to-Quality are weaker than those observed under the decreasing interest rate conditions. It is consistent with the observation that major crises within the analyzed sample happened during the periods of the interest rate decrease. Additionally, the strongest (on average) Flights-to-Quality, observed for the *ERA* upside ] 3%; 4%] range interval, could be interpreted as "financial euphoria"-provoked events as they are originated out of a strong growth in the appetite for risky assets already under conditions of an economic expansion. Due to a limited number of events obeying the condition of the *ERA* upside range inside the ] 3%; 4%] and ] 4%; ∞[ intervals (four events for each range), it is difficult to conclude anything regarding the efficiency ratio. Still under the aggregated view approach, the ] 3%; 4%] range represents the highest efficiency ratio in line with Table 3.3.22, and arguments below it.

***Efficiency Ratio dependence on the strength of the ERA downside move***

Additionally to the *ERA* upside moves dynamics for the entry alarm, the *ERA* downside moves dynamics, for the exit signals, is also addressed in Table 3.3.24 below. This study covers all the Flights-to-Quality exit alarms, independently on which metrics they were generated.

| ERA Downside Value | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | **Efficiency Ratio** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | **Efficiency Ratio** |
| ]0%; 1%] | 4 | 3.30% | 4.74% | 1.19% | **69.62%** | 4 | 3.30% | 4.74% | 1.19% | **69.62%** |
| ]1%; 2%] | 30 | 38.41% | 53.18% | 1.77% | **72.23%** | 30 | 38.41% | 53.18% | 1.77% | **72.23%** |
| ]2%; 3%] | 18 | 29.35% | 43.54% | 2.42% | **67.41%** | 18 | 29.35% | 42.77% | 2.38% | **68.62%** |
| ]3%; 4%] | 21 | 53.78% | 73.15% | 3.48% | **73.52%** | 21 | 53.78% | 65.43% | 3.12% | **82.19%** |
| ]4%; 5%[ | 15 | 37.85% | 55.81% | 3.72% | **67.82%** | 15 | 37.85% | 49.43% | 3.30% | **76.57%** |
| ]5%; ∞[ | 22 | 179.68% | 214.68% | 9.76% | **83.70%** | 22 | 179.68% | 204.62% | 9.30% | **87.81%** |

**Table 3.3.24**: Efficiency analysis of the Alarm Signal System as a function of the ERA metrics downside moves.

As one would expect, the average strength of the historically observed Flights-to-Quality exhibits a monotonic increase with the increase in the magnitude of the *ERA* downside moves. This is due to the fact that *ERA* metrics decrease within the Flight-to-Quality episodes as an appetite for risky assets deteriorates in such periods. As a good feature of the proposed Alarm Signal System, it can be mentioned that the most impactful Flights-to-Quality, corresponding to the *ERA* downside range ] 5%; ∞[ ), are treated the most efficiently, with the efficiency ratios of 83.70% (summation approach) and 87.81% (aggregated view approach).

***Efficiency Ratio dependence on the ERA downside move and the Interest Rate dynamics***

Additionally to the *ERA* downside moves dynamics, the risk-free interest rate behavior is included into the efficiency analysis of the exit alarm signals. The results are presented in Table 3.3.25 below. As it can be observed in this Table, the 17 historically observed strongest Flights-to-Quality, which corresponds to the periods of the interest rate decrease and the range of *ERA* downside of ] 5%; ∞[, are treated with the high efficiency ratios of 84.59% (summation approach) and 88.45% (aggregated view approach).

| ERA Downside Value/ Interest Rate | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | Efficiency Ratio | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Average Strength of Flights-to-Quality | Efficiency Ratio |
| **IR decreasing** | | | | | | | | | | |
| ]0%; 1%] | 2 | 1.99% | 2.34% | 1.17% | **85.04%** | 2 | 1.99% | 2.34% | 1.17% | **85.04%** |
| ]1%; 2%] | 16 | 22.34% | 28.88% | 1.81% | **77.35%** | 16 | 22.34% | 28.88% | 1.81% | **77.35%** |
| ]2%; 3%] | 9 | 17.40% | 27.06% | 3.01% | **64.30%** | 9 | 17.40% | 26.29% | 2.92% | **66.18%** |
| ]3%; 4%] | 12 | 32.01% | 44.35% | 3.70% | **72.18%** | 12 | 32.01% | 39.32% | 3.28% | **81.41%** |
| ]4%; 5%[ | 9 | 18.11% | 30.73% | 3.41% | **58.93%** | 9 | 18.11% | 26.00% | 2.89% | **69.65%** |
| ]5%; ∞[ | 17 | 148.84% | 175.96% | 10.35% | **84.59%** | 17 | 148.84% | 168.27% | 9.90% | **88.45%** |
| **IR increasing** | | | | | | | | | | |
| ]0%; 1%] | 2 | 1.31% | 2.40% | 1.20% | **54.58%** | 2 | 1.31% | 2.40% | 1.20% | **54.58%** |
| ]1%; 2%] | 14 | 16.07% | 24.30% | 1.74% | **66.13%** | 14 | 16.07% | 24.30% | 1.74% | **66.13%** |
| ]2%; 3%] | 9 | 11.95% | 16.48% | 1.83% | **72.51%** | 9 | 11.95% | 16.48% | 1.83% | **72.51%** |
| ]3%; 4%] | 9 | 21.77% | 28.80% | 3.20% | **75.59%** | 9 | 21.77% | 26.11% | 2.90% | **83.38%** |
| ]4%; 5%[ | 6 | 19.74% | 25.08% | 4.18% | **78.71%** | 6 | 19.74% | 23.43% | 3.91% | **84.25%** |
| ]5%; ∞[ | 5 | 30.84% | 38.72% | 7.74% | **79.65%** | 5 | 30.84% | 36.35% | 7.27% | **84.84%** |

**Table 3.3.25**: Efficiency analysis of the Alarm Signal System as a function of the ERA metrics downside move and the risk-free interest rate dynamics.

### *Efficiency Ratios of the Entry Alarm Signals*

There are three groups of entry alarm signals, which compose the proposed Alarm Signal System, namely, the *ERA* upside moves, the *SAA* downside moves, and the *ECA/2* upside moves. The efficiency analysis of these groups is performed group-by-group using the cumulative strength of the historically observed Flights-to-Quality over 1998 – 2010 and the cumulative strength of the would-be Flights-to-Quality which are warned of by the respective entry alarm signal. Additionally, the total efficiency ratio for a selected metrics is expressed in percentage of the cumulative impact of all the Flights-to-Quality independently on which metrics the alarm signals were generated. It characterizes a relative importance of the chosen metrics for a generating of the entry signals while compared to others. Table 3.3.26 represents outcomes of this analysis.

| Entry Signal Group | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the Group)** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the Group)** |
| ERA ↑ | 89 | 264.42% | 345.04% | **58.49%** | **76.63%** | 89 | 264.42% | 326.85% | **61.91%** | **80.90%** |
| SAA ↓ | 16 | 68.16% | 89.09% | **15.08%** | **76.51%** | 16 | 68.16% | 82.35% | **15.96%** | **82.77%** |
| ECA/2 ↑ | 5 | 9.79% | 10.97% | **2.17%** | **89.24%** | 5 | 9.79% | 10.97% | **2.29%** | **89.24%** |

**Table 3.3.26**: Efficiency analysis of the Entry Alarm Signals by the asset appetite metrics, used to generate an entry signal.

As it could be seen from Table 3.3.26 above, the *ERA* upside metrics is the most efficient as it allows to warn of 58.49% (summation approach) and 61.91% (aggregated view approach) of the total observed cumulative strength of the historically observed Flights-to-Quality within the analyzed period. Additionally, the number of Flights-to-Quality being delimited by this ERA↑ group considerably exceeds the quantity of the events warned of by the other groups. As it could be easily computed, 77.40% of the total number of the historically observed Flights-to-Quality are warned of by the *ERA* upside metrics group. All this allows to consider the entry signals based on the *ERA* upside move metrics as being the most important among the three alarm signal groups proposed here. But if only the strength of historically observed Flights-to-Quality being delimited by the respective entry alarm signal group is considered, the *ECA/2* metrics, measuring total asset appetite, appears to be more accurate than others. Nevertheless, *ERA* and *SAA* groups also present efficiency ratios above 75%.

Another consideration could be insightful for the comprehension of a nature of Flights-to-Quality. That is, if the entry signal warning of an upcoming event is generated based on the *ERA* metrics upside move, one could think of this Flight-to-Quality as of an event originated by the reassessment of the risk, related to the holding of the risky assets, i.e. *EM* risk-reassessment-driven events.

On the other hand, if the entry signal alarming an approaching episode is produced based on the *SAA* metrics downside move, this Flight-to-Quality is rather originated by the necessity to rapidly create a value in at least one part of the investment universe, the safe one. Thus, one could think of this event as of *UST*-driven occurrence aimed at stopping a joint underperformance in both, the safe and risky parts of the investment universe.

Additionally, the alarms generated based on the *ECA/2* metrics upside moves, could be ascribed to reaching unsustainable levels of financial investments (both, in risky and safe assets) as opposed to a purchase of/ investment in non-financial assets, which happens relatively rarely, but when happens, is treated with a great accuracy as evidenced in Table 3.3.26.

In order to analyze the accuracy within each group of entry signals considered alone, the two discussed above efficiency ratios are calculated for the each three situations occurring in the *ERA* and *SAA* groups, namely:

- *ERA* (the appetite for risky assets) surpasses up previously observed local maxima of investors´ appetites, either for risky (*ERA*), safe (*SAA*), or the totality of assets (*ECA/2*). In respect to this case of the primary metrics (*ERA*↑), whose behavior is analyzed here, there are three secondary metrics, *SAA*, *ECA/2*, and *ERA* itself, which are taken for comparison.

- *SAA* (the appetite for safe assets) surpasses down previously observed local minima of investors´ appetites, either for risky *(ERA)*, safe *(SAA)*, or the totality of assets *(ECA/2)*. In the case of the primary metrics *SAA*, whose behavior is analyzed here, also there are three secondary metrics, *ERA*, *ECA/2*, and *SAA* itself, which could be taken for comparison.

The results of these analyses are outlined in Table 3.3.27 and Table 3.3.28 respectively.

The *ECA/2* metrics has only one situation, when it surpasses up its previously observed local maximum, thus this analysis is not suitable for this metrics.

| **ERA Group: Entry Signals Secondary Metrics** | **Summation Approach** | | | | | **Aggregated View Approach** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the line)** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the line)** |
| ERA | 79 | 235.35% | 308.84% | **52.06%** | **76.20%** | 79 | 235.35% | 290.65% | **55.10%** | **80.97%** |
| SAA | 4 | 18.03% | 23.15% | **3.99%** | **77.88%** | 4 | 18.03% | 23.15% | **4.22%** | **77.88%** |
| ECA/2 | 6 | 11.04% | 13.05% | **2.44%** | **84.60%** | 6 | 11.04% | 13.05% | **2.58%** | **84.60%** |

**Table 3.3.27**: Efficiency analysis for the ERA metrics group by the secondary metrics used to generate the entry alarm signals.

| SAA Group: | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Entry Signals Secondary Metrics | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Efficiency Ratio, (% of Total Impact) | Efficiency Ratio (within the line) | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | Efficiency Ratio, (% of Total Impact) | Efficiency Ratio (within the line) |
| SAA | 13 | 59.22% | 74.86% | **13.10%** | **79.11%** | 13 | 59.22% | 68.12% | **13.86%** | **86.93%** |
| ERA | 1 | 1.60% | 3.02% | **0.35%** | **52.98%** | 1 | 1.60% | 3.02% | **0.37%** | **52.98%** |
| ECA/2 | 2 | 7.34% | 11.21% | **1.62%** | **65.48%** | 2 | 7.34% | 11.21% | **1.72%** | **65.48%** |

**Table 3.3.28**: Efficiency analysis for the SAA metrics group by the secondary metrics used to generate the entry alarm signals.

As it can be concluded from Table 3.3.27 above, the major part of Flights-to-Quality (68.70% of the complete set of the occurrences) happened after the *ERA* metrics becomes more positive than its proper recently observed pronounced local maximum. As expected, the efficiency ratio, while calculated in relation to the total strength of all *ex-post* identified Flights-to-Quality, for this pair: primary *ERA* upside and secondary *ERA* local maximum metrics, is also considerably higher than for other secondary metrics within the *ERA*-based entry alarm signal group. This is an important result as historically the majority of the Flights-to-Quality happen when the appetite for risky asset is rather exaggerated climbing above its previously observed local maximum. Nevertheless, the accuracy for the discussed pair of *ERA* metrics, calculated in respect to the strength of the corresponding historically observed Flights-to-Quality, warned of by this pair generated alarm signals is lower than for the other secondary metrics within *ERA* upside group, but it still represents a significant value of 76.20%.

Differently to the *ERA*-*ERA* metrics pair, as it can be seen in Table 3.3.28 above, the *SAA*-*SAA* metrics pair results in the highest efficiency ratio while compared to the other secondary metrics of the *SAA* entry signal group.

***Efficiency Ratios of the Exit Alarm Signals***

There are also three groups of exit alarm signals, which complete the proposed Alarm Signal System, namely, the *ERA* downside moves, the *SAA* upside moves, and the *ECA/2* downside moves. The efficiency analysis of these groups is performed group-by-group using the total cumulative strength of the historically observed Flights-to-Quality over 1998-2010 and the cumulative strength of would-be Flights-to-Quality which are warned of by the respective exit alarm signal group. Additionally, the total efficiency ratio for a selected metrics is expressed in percentage of the cumulative impact of all the Flights-to-Quality, independently on which metrics the alarm signals were generated. It characterizes a relative importance of the chosen metrics for a generation of the exit signals while compared to others. Table 3.3.29 represents outcomes of this analysis.

| Exit Signal Group | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the Group)** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the Group)** |
| ERA ↓ | 100 | 305.07% | 398.82% | **67.49%** | **76.49%** | 100 | 305.07% | 375.97% | **71.42%** | **81.14%** |
| SAA ↑ | 8 | 34.68% | 43.15% | **7.67%** | **80.37%** | 8 | 34.68% | 41.07% | **8.12%** | **84.44%** |
| ECA/2 ↓ | 2 | 2.62% | 3.13% | **0.58%** | **83.71%** | 2 | 2.62% | 3.13% | **0.61%** | **83.71%** |

**Table 3.3.29**: Efficiency analysis of the Exit Alarm Signals by the asset appetite metrics, used to generate an exit signal.

As it can be seen from Table 3.3.29 above, the *ERA* downside metrics is the most efficient as it allows to warn of 67.49% (summation approach) and 71.42% (aggregated view approach) of the total observed cumulative strength of the historically observed Flights-to-Quality within the analyzed period. Additionally, the number of the Flights-to-Quality being "terminated" by this *ERA*↓ group considerably exceeds the quantity of the events delimited by the other groups. As it could be easily computed, 86.96% of the total number of the historically observed Flights-to-Quality are warned of by the *ERA* downside metrics group. All these allow to conclude that the exit signals based on the *ERA* downside move metrics are the most important ones. But if only the strength of historically observed Flights-to-Quality being delimited by the respective exit alarm signal group is considered, the *ECA/2* metrics appears to be more accurate than others. Nevertheless, *ERA* and *SAA* groups also exhibit efficiency ratios above 75%.

In order to analyze the accuracy within each group of exit signals considered alone, the two discussed above efficiency ratios are calculated for the each three situations occurring in the *ERA* and *SAA* groups, namely:

- *ERA* (the appetite for risky assets) surpasses down previously observed local minima of investors´ appetites, either for risky (*ERA*), safe (*SAA*), or the totality of assets (*ECA/2*). In respect to this case of the primary metrics (*ERA*), whose behavior is analyzed, there are three secondary metrics, *SAA*, *ECA/2*, and *ERA* itself, which could be taken for comparison.

- *SAA* (the appetite for safe assets) surpasses up previously observed local maxima of investors´ appetites, either for risky *(ERA)*, safe *(SAA)*, or the totality of assets *(ECA/2)*. In the case of the primary metrics *SAA*, whose behavior is analyzed here, there are also three secondary metrics *ERA*, *ECA/2*, and *SAA* itself, which are taken for comparison.

The results of these analyses are outlined in Table 3.3.30 and Table 3.3.31 respectively.
The *ECA/2* metrics has only one situation, when it surpasses down its previously observed local minimum, thus this analysis is not considered for this group of metrics.

| ERA Group: | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Exit Signals Secondary Metrics | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the line)** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the line)** |
| ERA | 82 | 259.13% | 333.75% | **57.32%** | **77.64%** | 82 | 259.13% | 313.81% | **60.67%** | **82.58%** |
| SAA | 9 | 20.91% | 32.58% | **4.63%** | **64.18%** | 9 | 20.91% | 31.94% | **4.90%** | **65.47%** |
| ECA/2 | 9 | 25.03% | 32.49% | **5.54%** | **77.04%** | 9 | 25.03% | 30.22% | **5.86%** | **82.83%** |

**Table 3.3.30**: Efficiency analysis for the ERA metrics group by the secondary metrics used to generate the exit alarm signals.

| SAA Group: | Summation Approach | | | | | Aggregated View Approach | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Exit Signals Secondary Metrics | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the line)** | Number of Flights-to-Quality | Would-be Cumullative Strength | Observed Cumullative Strength | **Efficiency Ratio, (% of Total Impact)** | **Efficiency Ratio (within the line)** |
| SAA | 6 | 29.34% | 34.75% | **6.49%** | **84.43%** | 6 | 29.34% | 33.97% | **6.87%** | **86.37%** |
| ERA | 1 | 3.37% | 6.11% | **0.75%** | **55.16%** | 1 | 3.37% | 4.81% | **0.79%** | **70.06%** |
| ECA/2 | 1 | 1.97% | 2.29% | **0.44%** | **86.03%** | 1 | 1.97% | 2.29% | **0.46%** | **86.03%** |

**Table 3.3.31**: Efficiency analysis for the SAA metrics group by the secondary metrics used to generate the exit alarm signals.

As it can be concluded from the Tables above the major part of the Flight-to-Quality terminations (71.30% of the total number of the cases) happened after the *ERA* metrics becomes lower than its proper recently observed local minimum. The efficiency ratio for this pair: primary *ERA* downside and secondary *ERA* local minimum metrics, while calculated in relation to the total strength of all *ex-post* identified Flights-to-Quality, is also considerably higher than for other secondary metrics within the *ERA*-based exit alarm signal group. Thus, the majority of the Flight-to-Quality terminations occur when the appetite for risky asset is decaying below its previously observed local minimum.

The efficiency ratios (within the line) for the discussed *ERA-ERA* and *SAA-SAA* metrics based exit alarms, when are calculated in respect to the strength of the corresponding historically observed Flights-to-Quality, represent values above 75%, meaning that more than the three fourth of the Flights-to-Quality impact could be delimited on *ex-ante* basis with a help of exit signals of the Alarm Signal System.

***Timeliness of the Alarm Signal System***

The efficiency of the Alarm Signal System in terms of the timeliness of the generated alarm signals is analyzed as a lag between the date of the appearance of the entry signal and the historically observed Flight-to-Quality ignition and vice versa, and, by analogy, as an interval between the date of the exit signal and the respective Flight-to-Quality termination day. On average, over 1998 - 2010, the time scale mismatches between the entry signals and the Flight-to-Quality ignitions and between the exit signals and the Flight-to-Quality terminations are -1.94 working days and -1.21 working days, respectively. It means that majority of alarm signals appear prior to either ignition or termination dates. The two above numbers become -1.42 working days and -0.86 working days if the five cases of entry signals "outliers" and two cases of exit signals "outliers", both characterized by the mismatches superior to ten working days, are excluded from of the averaging procedures. Among 115 historically observed Flight-to-Quality the entry alarm signals coincide with the ignition days of events 38 times while the exit alarm signals coincide with the termination dates 69 times.

There are 67 cases when entry alarm signal was generated prior to the ignition of Flight-to-Quality, and there are only 5 cases when an entry alarm is delayed.

There are 38 cases when exit alarm signal was generated prior to the termination of Flight-to-Quality, and there are 3 cases when an exit alarm appears after the Flight-to-Quality is over.

#### 3.3.3.3. Conclusive remarks and insights

Prior to summarizing the main features of the described above Alarm Signal System and performing a brief conclusive survey of the results obtained by its application to delimiting Flight-to-Quality time frames, it is worth making a few comments. In a sense of the research flow, this study of the Alarm Signal System preceded the next Chapter 4, which is dedicated to the hedge strategies. Thus, the main intention of the exercise performed in the two previous sections was to illustrate the potential of the proposed Alarm Signal System not only for chosen individual events, but also for the whole range of Flights-to-Quality within the analyzed time interval 1998 – 2010. To assess this potential, the efficiency analysis of the Alarm Signal System was performed. This analysis, among others, had a target to estimate the cumulative strength of the Flights-to-Quality delimited on *ex-ante* basis. This cumulative strength is a measure of the total adverse impact of the Flights-to-Quality. As originated from the time frames delimited only by using the information available before the event, the adverse influence of these events can be addressed further on, in an actionable manner, via engineering appropriate hedge strategies.

The application of the Alarm Signal System permitted to delimit, using only the prior to the event data, the Flights-to-Quality with the total cumulative strength of 342.33%. On the other hand, the *ex-post* identified Flights-to-Quality with the event impact parameter (*EIP*) above 1% have the respective total cumulative strength of 452.04% within the same period 1998 – 2010. If one thinks of this percentage figure as of cumulative losses incurred (although then recovered from) over the 13 years, then the possibility to dynamically avoid at least a part of them reveals a huge potential to improve performance of the investments in the *EM* fixed income portfolios (hedged against the interest rate downside risk). Bearing in mind the lowest found efficiency ratio of the presented Alarm Signal System of 75.73%, which corresponds to the event impact parameter (*EIP*) above 1% (see Table 3.3.18), one can expect an annual potential improvement of 26.33% (342.33%/ 13 years). It is superior to the average annual yield paid by the *EM* debt, which is about 9.71% (as can be calculated using *EMBI* index return over the analyzed 13 years).

Another interesting result of the Alarm Signal System analyses is that the efficiency ratio grows with the increase in the event impact parameter (see Table 3.3.18). It means that, on average, the greater the strength of a Flight-to-Quality, the greater is the accuracy with which the Alarm Signal System delimits it.

Additionally, the application of the Alarm Signal System supports the explanation of Flight-to-Quality events from the asset appetites considerations. As it was demonstrated in terms of percentage of total impact, see Tables 3.3.26 and 3.3.29, the most accurate metrics, which is also the most commonly employed, is the Expectation-adjusted Relative Appetite (*ERA*), which measures investor´s willingness to hold risky assets.

At this point, the study passes from the initial description and analyses of the Alarm Signal System to the research of its applicability to producing dynamical responses for withstanding financial instability in a chronological perspective, i.e. to the dynamic hedge strategies and timely financial polices´ responses.

# 4. Application of the Alarm Signal System

The Alarm Signal System for delimiting Flights-to-Quality on *ex-ante* basis, which was proposed and studied in the previous Chapter, is applied further on to the development of the diverse hedge strategies and to improvement of the timeliness of the financial policies to withstand financial instability.

## 4.1. Application to the Hedge Strategies

In this part an application of the Alarm Signal System to the interest rate risk hedge practices is performed and discussed. As in the previous Chapter, the *EM* fixed income portfolio, described by the *EMBI* index is considered. As an example of the interest rate risk hedge, the short positions in the *UST* bonds, which can be described by the already used *ITRROV* index, are employed. This represents one of the simplest and cheapest approaches to the interest rate risk hedging. It is widely used by many fund managers and investment banks for hedging their fixed income portfolios against possible downsides related to the interest rate dynamics and also attending requirements by the regulators, such as country central banks or other financial authorities, in respect to the interest rate risk management.

### 4.1.1. Concept of the Interest Rate Risk Hedge

Financial institutions can hedge interest rate risk in various ways. But their main focus remains the same. It is to reduce an interest rate risk by taking a position opposite of what they already have in their portfolio. Interest rate risk hedge is nothing but a strategy designed to reduce investment risk using "*call*" options, "*put*" options, "*short*" positions, or futures contracts. A hedge can help lock in existing profits. Its purpose is to reduce the potential volatility of a portfolio, by reducing the risk of loss.

A common example of a simple hedge strategy is short positions in *UST* bonds. It is worth noting that the entering in the *UST* short positions are practiced due to many reasons, the most important of which are the following: high liquidity, big trading volumes and low transactional costs of these instruments in comparison, for example, with futures, options and other derivatives. Thus, it becomes easy to change one´s short exposure according to the growth or shrinking of the hedged portfolio.

A successful hedge strategy must be based on an understanding of the relationship between investment risk and return of the analyzed portfolio. Thus, at this point it is worth commenting on the essence of the interest rate risk in respect to the fixed income portfolio.

Fixed income securities that pay a specified rate of interest (bonds, for example) lose some of their value if interest rates rise. The market prices of outstanding securities of this type fall when rates rise because buyers won't pay the bond's face value due to the difference between the interest rate of the existing security and the higher rate available from a comparable newly issued security. An illustrative example of an interest rate risk profile of a stand-alone bond is presented in Figure 4.1.1.

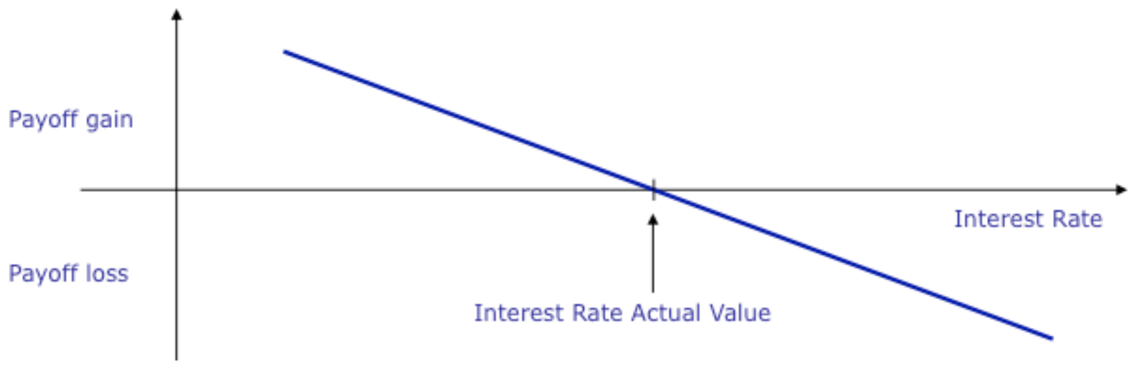



**Figure 4.1.1**: Illustrative example of an interest rate risk profile of a stand-alone bond.

It should be noticed that real interest rate risk profiles of the securities are not linear. Additionally, while individual securities are grouped into portfolios, this can lead to quite unpredictable results due to the effects of the non-linearity of the individual profiles and the effects of their superposition.

Therefore, the first step in an elaboration of the interest rate risk hedge strategy would be a construction of the interest rate risk profile for the portfolio to be hedged. That is, one needs to determine how the total value of the considered fixed income portfolio changes under increase/ decrease in interest rates. An illustrative example of possible interest rate risk profiles is given in Figure 4.1.2 below. For the long portfolios, their profiles are extended from the left-hand side upper quadrant to the right-hand side bottom one, meaning that increase in interest rate results in value destruction.

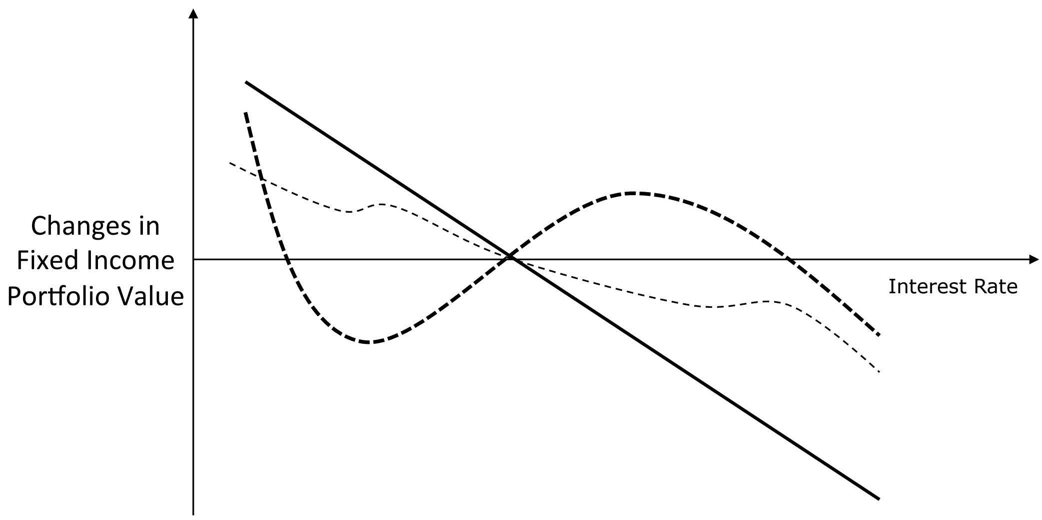



**Figure 4.1.2**: Illustrative examples of possible interest rate risk profiles for diverse portfolios.

However, such "by-the-book" approach is rarely applied by investment practitioners. The main reasons of that are the costs involved in the construction of the portfolio risk interest rate profile, as well as precision and trustworthiness of such profile. Although the historic behavior of assets is the best proxy of their further paths, the past performance of financial assets does not guarantee their future behavior.

Therefore, the simplest case of the interest rate risk hedge, considered here, namely short positions in *UST* bonds (covering the *EM* portfolio), is based on the simplified assumption of a "*perfect*" correlation between *UST* and *EM* yields′ moves which, of course, is not always true, as it was already shown in the previous Chapters. In fact, the spread varies with time, sometimes resulting in Flight-to-Quality events, which are the subject of this research.

Below a concept of the aforementioned simplest hedge strategy is explained in more detail by means of the following example. The model portfolio consisting of $100 in Emerging Market bonds, hedged by $100 short position in *UST* bonds is considered, as depicted in Figure 4.1.3.


**Figure 4.1.3**: Model portfolio and its interest rate risk hedging.

*UST* short positions are created by short selling. Investor sells short by "*borrowing*" *UST* from another investors, then selling them. By selling short, one is hoping to profit from a future drop in the *UST* price. Investor profits when the *UST* price falls and he is able to buy back the *UST* (to repay to the owner) for less than his sale price. Investor loses money if the price rises and has to buy for more than his sales price.

It is also possible to protect an *EM* portfolio profit by short selling *EM* bonds investor already own. (This possibility will be addressed in the next parts.)

As represented in Figure 4.1.3 above, *EM* bonds portfolio of an initial value of $100 is considered. Its interest rate risk is mitigated by short positions in the *UST* bonds also of the same initial value of $100. As the average yield of *EM* bonds is higher than the one of *UST* bonds, such hedged portfolio provides a stable contributing inflow of net interest income, in an absence of Flight-to-Quality events, but still potentially suffers from negative shocks of asset prices and positive shocks of hedge prices during Flight-to-Quality episodes.

Considering an ideal case with no Flights-to-Quality, the functioning of the interest rate risk hedge can be represented by a so-called square position as depicted on Figure 4.1.4 below.

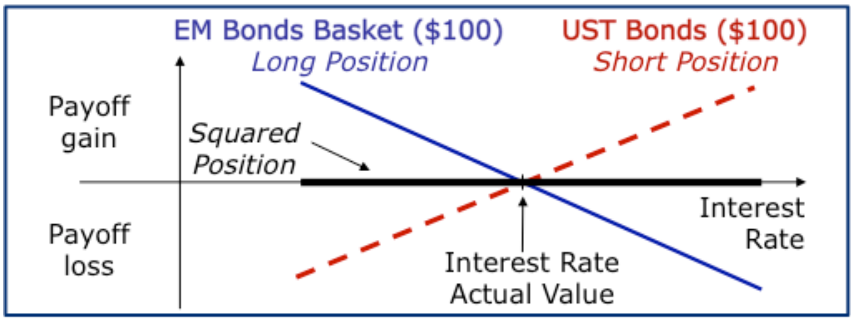



**Figure 4.1.4**: Interest rate risk hedge at work resulting in a square position.

As illustrated in Figure above, a joint effect of the long and the short positions of the same nominal value result in the targeted square position, represented by a thick solid line, and meaning that the value of this hedged portfolio is insensitive to the interest rate changes.

### 4.1.2. Returns of the *EM* Portfolio under Static Hedge based on short *UST*

The static interest rate hedge strategy is applied to the *EM* bond portfolio, described by the *EMBI* index. The short *UST* positions are modeled by *ITRROV* index. The final annual return of the hedged portfolio is calculated by a subtraction of the *ITTROV* annual return from the respective annual return of the *EMBI* index. This study is performed on a calendar year basis over 1998 – 2010 and presented in Table 4.1.1 below. For simplicity reasons, no transaction costs for adjusting nominal of the short and long positions at the beginning of a year are considered.

| Year | ITRROV Annual Return | EMBI Annual Return | EM hedged by UST (EMBI - ITRROV) |
|---|---|---|---|
| 1998 | 9.74% | -11.82% | -21.56% |
| 1999 | -2.46% | 24.18% | 26.64% |
| 2000 | 13.29% | 14.41% | 1.12% |
| 2001 | 6.86% | 1.36% | -5.51% |
| 2002 | 11.54% | 13.12% | 1.58% |
| 2003 | 2.26% | 25.66% | 23.40% |
| 2004 | 3.48% | 11.73% | 8.25% |
| 2005 | 2.80% | 10.73% | 7.93% |
| 2006 | 3.10% | 9.88% | 6.78% |
| 2007 | 8.99% | 6.28% | -2.72% |
| 2008 | 14.88% | -10.97% | -25.85% |
| 2009 | -4.51% | 28.26% | 32.76% |
| 2010 | 5.82% | 12.04% | 6.22% |

**Table 4.1.1**: Returns of the EM model portfolio statically hedged by short positions in UST.

As can be seen from Table 4.1.1, the results of *EM* bonds portfolio statically hedged by short positions in *UST* represent considerable volatility as they significantly vary from year to year. Additionally, there are other indications that the static hedge is not ideal for the pair of the *EMBI – ITRROV*. For example, these indexes´ returns for the calendar year periods differ a lot. This means that even if in the beginning of the year the long and short positions were adjusted, at the end of the year a considerable mismatch exists between the short and long positions, making the interest rate risk hedge less effective. Another feature is related to the fact that during a problematic for *EM* years, namely 1998, 2001, 2007 and 2008, the returns of the *UST* basket were positive and superior to the returns of the *EMBI* bonds basket, resulting in the negative returns of the hedged portfolio as a whole. These results can be ascribed to the existence of Flights-to-Quality, requiring more sophisticated approaches to the interest rate risk hedge, as, for example, dynamic hedge strategies, which will be addressed further on.

### 4.1.3. Concept of the Dynamic Interest Rate Risk Hedge

During a Flight-to-Quality, for example, in a period of a decrease in the interest rate of risk-free assets, this move is not accompanied by the similar behavior of the *EM* bond portfolio yield. Even more than that, the *EM* portfolio does not behave any more as a long position in respect to the *UST* yield. That means that the EM portfolio is not described anymore by a solid line with negative slope, marked as "*Long Position*" in Figure 4.1.5 below. Rather its value diminishes with the decrease in *UST* yield. Henceforth, the *EM* portfolio begins to behave as a short position during the Flight-to-Quality as it is depicted by dotted line with positive slope. So, investor loses his money in his risky actives (*EM* securities basket) when *UST* yield goes down during the Flight-to-Quality phenomena.

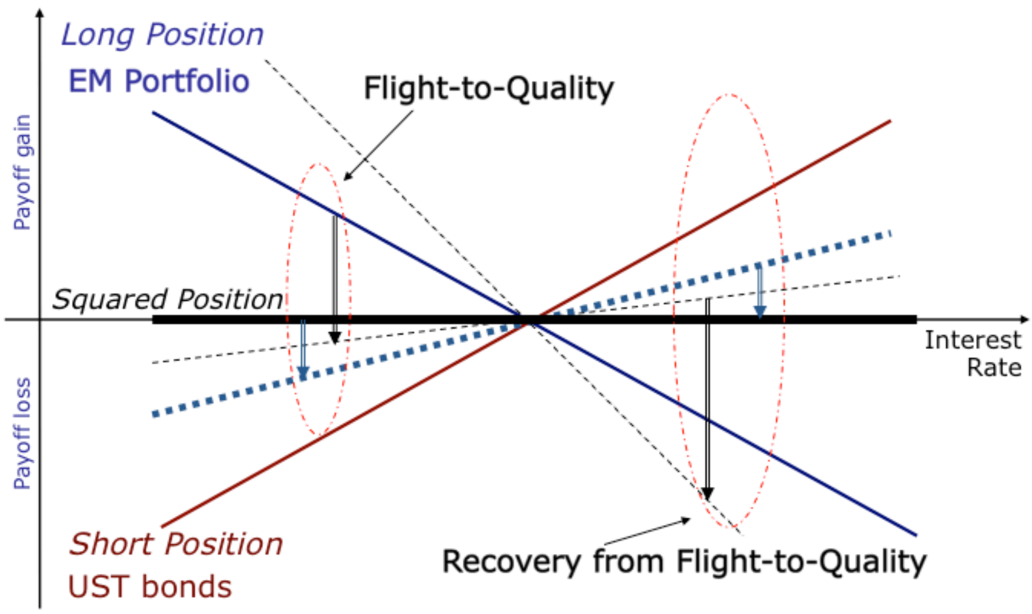



**Figure 4.1.5**: Interest rate risk profiles dynamics within and after Flight-to-Quality.

On the other hand, under the Flight-to-Quality circumstances, for example, when *UST* interest rate falls, any short position in the *UST* bonds, depicted by the solid line with negative slope marked as "*Short Position*" in Figure 4.1.5, also results in value destruction.

Consequently, the static hedge strategy based on short positions in *UST* bonds also makes an investor to lose his money under a Flight-to-Quality. This time the loss is evidenced on the side of his liabilities.

That is why, under Flight-to-Quality conditions, investors who apply static hedge strategy, lose their money on both sides: on the side of assets and on the side of liabilities. So, Flight-to-Quality phenomena are very undesirable in this sense, and require hedge strategies being modified in accordance with market conjuncture. This is nothing but dynamic hedge strategies.

In order to demonstrate how the application of the Alarm Signal System to hedge strategies can influence investment results, the following simple dynamic hedge strategy could be considered.

Firstly, on the date of the appearance of the entry alarm signal, the total short position in *UST* bonds is closed and switched to the long position until the exit signal is generated, see Figure 4.1.6 below. So, the long position in *UST* bonds remains until the termination of the would-be Flight-to-Quality delimited on *ex-ante* basis. When the exit signal appears, it is newly switched to the short position in *UST* bonds.

Secondly, on the date of the appearance of the entry alarm signal, the total long position in *EM* bonds is closed and switched to the short position until the exit signal is generated, see Figure 4.1.6 below. So, the short position in *EM* bonds remains until the termination of the would-be Flight-to-Quality delimited on *ex-ante* basis. When the exit signal appears, it is newly switched to the long position in *EM* bonds.

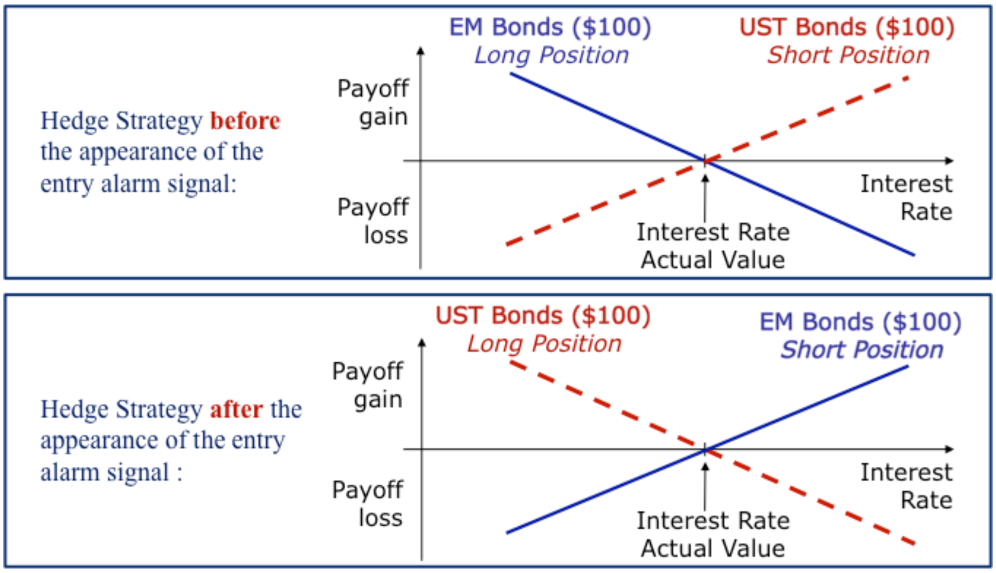



**Figure 4.1.6**: Dynamic hedge strategy asset allocations altered by the entry alarm signal.

The alteration of the dynamic hedge strategy introduced by the entry alarm signal is removed by the exit alarm signal warning of the termination of a Flight-to-Quality. So, the system returns to its initial stage, as depicted in Figure 4.1.7.

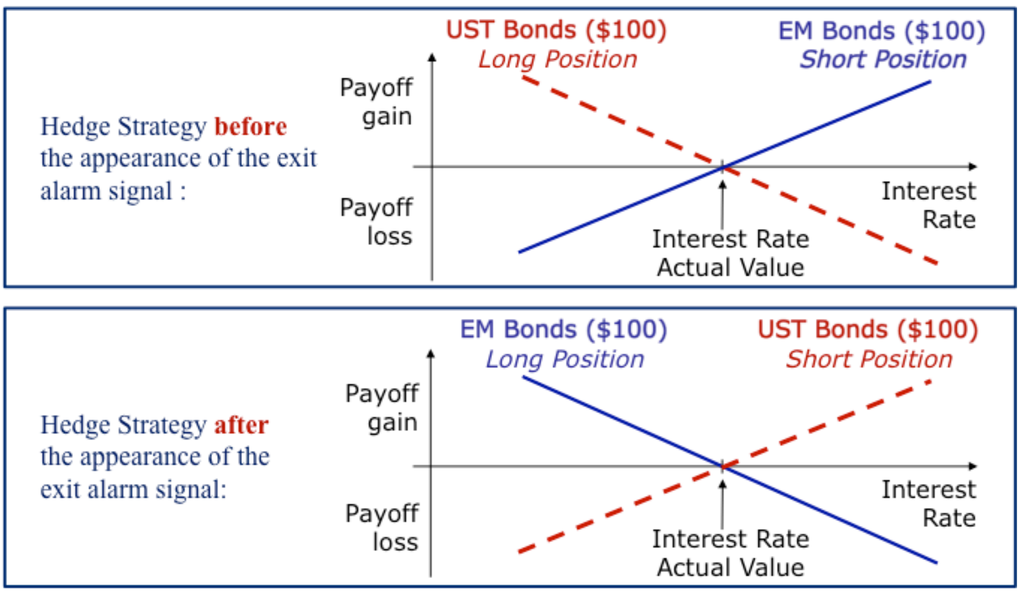



**Figure 4.1.7**: Dynamic hedge strategy asset allocations altered by the exit alarm signal.

Further on, this, the simplest, case of interest rate risk dynamic hedge is applied to the pair of the *EMBI – ITRROV* assets baskets over the period 1998 – 2010.

### 4.1.4. Returns of the *EM-UST* Portfolio: Dynamic Hedge without Transaction Costs

The simplest case of the dynamic interest rate hedge strategy is applied to the pair of the *EM* bonds and the *UST* bonds portfolio, offering a possibility of switching between the long and the short positions for both, the *EM* and the *UST* bonds baskets.

Figure 4.1.8 is presented below in order to illustrate an impact of the switching (inversion of the positions), or the difference between the static and the dynamic interest rate risk hedges. The dynamic hedge strategy is based on the entry and exit alarms generated by the proposed Alarm Signal System. The *EM* and the *UST* fixed income assets baskets are modeled by *EMBI* and *ITRROV* indexes, respectively.

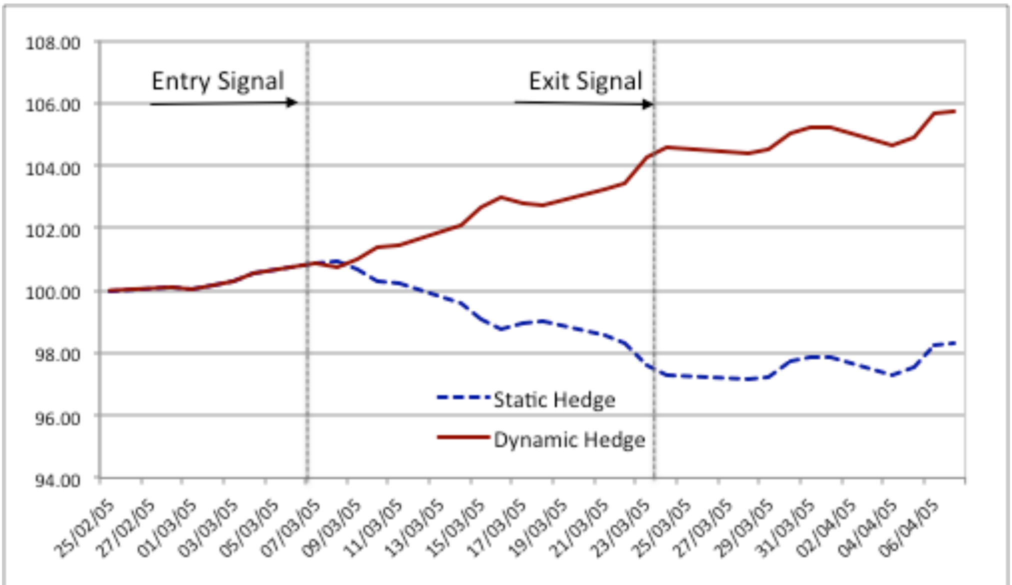



**Figure 4.1.8**. EM (EMBI) – UST (ITRROV) portfolio under static and dynamic hedge strategies over 25.02.2005 – 07.04.2005.

As can be seen from Figure 4.1.8, the switching between the long and the short positions on the date of the entry signal (07.03.2005) permits to revert otherwise negative performance of the portfolio (under the static hedge strategy). On the date of the exit alarm, the new switching reestablishes the original assets and liabilities allocation. In this manner, under the dynamic hedge strategy, the $100 invested, in this example on 25.02.2005, in the *EM* portfolio, hedged by the short position in the *UST* bonds, become $105.73 on 07.04.2005. Otherwise, under the static hedge strategy, the negative impact of the Flight-to-Quality transforms the initial investment of $100 into $98.32.

Following the considered above example, each annual return of the hedged portfolio is calculated as a sum of the returns related to the *EMBI*-long/ *UST*-short pair, followed by the returns of the switched *EMBI*-short/*UST*-long pair, then followed by the newly switched *EMBI*-long/ *UST*-short pair, and so on within the calendar years over 1998 – 2010. The Alarm Signal System is used for generation of the alarm signals warning of a necessity of switching.

The results are presented in Table 4.1.2 below. At this stage, for simplicity reasons, no transaction costs for the long-short and short-long switches are considered.

| | Annual Returns | | |
|---|---|---|---|
| Year | Static Hedge: EM hedged by UST (EMBI - ITRROV) | Dynamic Hedge: Long/Short Switching based on Generated Alarms | Dynamic Hedge: Long/Short Switching on F-t-Q Ignition and Termination dates |
| 1998 | -21.56% | 180.02% | 371.12% |
| 1999 | 26.64% | 136.57% | 186.39% |
| 2000 | 1.12% | 74.93% | 96.53% |
| 2001 | -5.51% | 137.62% | 190.85% |
| 2002 | 1.58% | 85.10% | 106.24% |
| 2003 | 23.40% | 53.14% | 65.38% |
| 2004 | 8.25% | 36.03% | 49.39% |
| 2005 | 7.93% | 20.11% | 26.14% |
| 2006 | 6.78% | 14.28% | 26.88% |
| 2007 | -2.72% | 32.23% | 40.50% |
| 2008 | -25.85% | 118.47% | 157.38% |
| 2009 | 32.76% | 70.05% | 85.48% |
| 2010 | 6.22% | 39.69% | 68.20% |

**Table 4.1.2**: Comparison of the static and dynamic interest rate risk hedge strategies.

Additionally, in the right hand side column of the Table 4.1.2 above the results of the dynamic hedge strategy, calculated based on the ignition and termination dates of historically observed Flights-to-Quality, are presented. They illustrate a potential for improvement of the Alarm Signal System in order to obtain a better match between the generated on *ex-ante* basis alarm signals and the initial and final dates of historically observed Flights-to-Quality, as identified on *ex-post* basis.

The results presented above in Table 4.1.2, are consistent with each other as no transaction costs are included into consideration in any of the hedge strategies. Still they should be analyzed rather from the qualitative than from the quantitative perspective. For instance, the huge improvement in portfolio performance is possible in principle to be obtained by passing from the static hedge to the proposed here dynamic one, which is based on the Alarm Signal System. In each line the values in the middle column are much superior to those from the column on the left.

While comparing the middle column to the column on the right, once again the performance for all the years are improving from the left to the right. On average, the values in the right column (ideal "perfect" signals coinciding with the historically observed ignition and termination dates) present an improvement of order above 40% in respect to the values in the middle column (based on the dynamic hedge based on the proposed Alarm Signal System). Thus, there is a challenge of further improvement of the process aimed to delimit Flights-to-Quality on *ex-ante* basis.

On the other hand, more realistic analysis of the dynamic hedge strategies must include the transactional costs for the switching between short and long positions and for adjustments between nominal values of assets and liabilities.

### 4.1.5. Returns of the *EM-UST* Portfolio: Dynamic Hedge with Transaction Costs

In this part a study of the influence of the transaction costs on the returns of the dynamically hedged *EM-UST* portfolio is performed. As expected, increase in the transaction costs diminishes otherwise possible gains under the investigated dynamic hedge strategy based on switching between the long and the short positions.

Prior to presenting results, an inclusion of transaction costs into the calculation of the returns is discussed in more detail. When a Flight-to-Quality entry alarm signal is generated, the nominal of the long position in *EMBI* is altered by the amount representing gains or losses occurred, since the end of the previous would-be Flight-to-Quality in the short position in *UST* bonds. Then, the resulting amount is reduced by the total value of the transaction costs, relative to both, switching from *EMBI* long to *EMBI* short position and closing *UST* short and entering in a long position in *UST* bonds, described by *ITRROV* index. The value obtained as a result of this step becomes the new nominal value for both, the short *EMBI* and the long *ITRROV* positions. These positions, after being inverted, behave contrary to their respective indexes´ moves until a new switching at the date of an appearance of the exit alarm signal.

During this second switching, once again the gains or losses occurred in the long *UST* position since the date of the entry alarm signal are accounted for by alteration of the nominal of the *EMBI* position. Than, the resulting amount is newly adjusted by the total value of the transaction costs, relative to both, switching from *EMBI* short to *EMBI* long position and closing *UST* long and entering in a short position in *UST* bonds.

It is worth noting that to make possible a switching between short and long positions in any instrument, the necessary condition is that the market for the chosen instrument should be liquid and represent a sufficient depth allowing for unstressed liquidation and purchase of assets in question. One is to agree that it is a case for *UST* bonds. For instance, among causes underlying their status of safe haven instruments is extremely high liquidity and vast trading volumes. It is also the case for *EM* government bonds.

The proprietary analysis of transaction costs of the 15 most liquid *EM* securities is performed in April 2012 and reveals that the average value of the bid-ask spread over mid price is about 0.7% (with minimum of 0.21% for the Russian Federation and maximum of 1.53% for the Republic of Colombia). It is worth mentioning that current market situation is not completely normalized in respect to pre-crises conditions. On the other hand, under financial turmoil one can expect transaction costs to considerably increase. Thus, for the sake of modeling for *EM* transaction costs are chosen the following values: 0.5%, 1.0% and 1.5%. The corresponding *UST* bonds transaction costs are assumed to be 0.25%, 0.5%, and 0.75%, respectively.

The annual results for the considered dynamic hedge strategy with the above stated transaction costs are presented in Table 4.1.3.

| Year | Annual Returns | | | | |
|---|---|---|---|---|---|
| | Static Hedge | | Dynamic Hedge | | |
| | EMBI Long (no Hedge, no Transacton Costs) | EM hedged by UST (EMBI - ITRROV; no Transaction Costs) | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) |
| 1998 | -11.82% | -21.56% | 111.59% | 82.23% | 56.77% |
| 1999 | 24.18% | 26.64% | 101.53% | 69.83% | 42.96% |
| 2000 | 14.41% | 1.12% | 29.71% | 5.40% | -14.56% |
| 2001 | 1.36% | -5.51% | 68.51% | 36.42% | 10.24% |
| 2002 | 13.12% | 1.58% | 29.28% | 9.58% | -7.24% |
| 2003 | 25.66% | 23.40% | 38.03% | 26.06% | 15.04% |
| 2004 | 11.73% | 8.25% | 29.71% | 21.24% | 13.28% |
| 2005 | 10.73% | 7.93% | 13.63% | 10.17% | 6.79% |
| 2006 | 9.88% | 6.78% | 10.21% | 5.11% | 0.21% |
| 2007 | 6.28% | -2.72% | -4.24% | -15.73% | -25.91% |
| 2008 | -10.97% | -25.85% | 57.59% | 38.16% | 20.93% |
| 2009 | 28.26% | 32.76% | 24.83% | 6.64% | -9.00% |
| 2010 | 12.04% | 6.22% | 4.53% | -9.45% | -21.65% |

**Table 4.1.3**: Comparison of the static and dynamic hedge for diverse ranges of transaction costs.

As can be verified by consecutively applying these annual returns from the Table 4.1.3 to a unitary amount of the initial 1998 investment of, for example, $100, the transaction costs higher than 0.5% for *UST* and 1.00% for *EMBI* become prohibitive for dynamic hedge strategies implementations. The considered dynamic hedge strategy, with the inferior transaction costs, is providing better results than the static investment strategies. The results of the described exercise are presented in Table 4.1.4.

| Year | Portfolio Size (initial investment $100) | | | | |
|---|---|---|---|---|---|
| | Static Hedge | | Dynamic Hedge | | |
| | EMBI Long (no Hedge, no Transacton Costs) | EM hedged by UST (EMBI - ITRROV; no Transaction Costs) | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) |
| 1998 | 88.18 | 78.44 | 211.59 | 182.23 | 156.77 |
| 1999 | 109.50 | 99.34 | 426.41 | 309.48 | 224.11 |
| 2000 | 125.28 | 100.45 | 553.08 | 326.20 | 191.48 |
| 2001 | 126.98 | 94.92 | 932.00 | 445.01 | 211.09 |
| 2002 | 143.63 | 96.42 | 1204.90 | 487.62 | 195.80 |
| 2003 | 180.49 | 118.98 | 1663.07 | 614.69 | 225.26 |
| 2004 | 201.66 | 128.80 | 2157.10 | 745.28 | 255.17 |
| 2005 | 223.30 | 139.02 | 2451.14 | 821.07 | 272.50 |
| 2006 | 245.36 | 148.44 | 2701.45 | 863.06 | 273.06 |
| 2007 | 260.75 | 144.41 | 2586.83 | 727.30 | 202.32 |
| 2008 | 232.15 | 107.08 | 4076.53 | 1004.84 | 244.66 |
| 2009 | 297.75 | 142.16 | 5088.60 | 1071.54 | 222.63 |
| 2010 | 333.60 | 151.01 | 5319.01 | 970.24 | 174.42 |

**Table 4.1.4:** Evolution of the initial investment of $100 over 1998 – 2010 for static and dynamic hedge for diverse transaction costs.

As can be seen in Table above, the lowest transaction costs (0.25% for *UST* and 0.50% for *EMBI*) lead to unrealistically huge portfolio growth and are presented here only for the sake of comparison.

### 4.1.6. *EM* Portfolio Hedged by Shortening the *EM* Positions within Flights-to-Quality

As it was already mentioned in the beginning of this Chapter, it is also possible to protect the *EMBI* portfolio by assuming the short positions in the *EM* assets an investor already own. This can be also comprehended as a purchase of the inverse *EMBI* index certificate while having long *EMBI* index position. Here, the inverse index certificate is considered to lose as many index points as the direct *EMBI* index gains and vice versa. This is equivalent to the so-called square position in *EMBI*.

This square position in *EMBI* will be taken not always but within would-be Flight-to-Quality intervals only delimited on *ex-ante* basis by the Alarm Signal System. This basic *EMBI* related strategy could be unfolded thrice according to the following chosen strategies for *UST* positions. The first is a simple maintenance of the static *UST* shot position. In this case, the transaction costs are not applicable to the *UST* short position. The second unfolding is related to the cancelling *UST* short position out within the would-be Flight-to-Quality intervals and reestablishing it after a would-be Flight-to-Quality termination. The third sub-strategy is the switching of *UST* exposition from the short to the long position at the date of the entry alarm signal appearance and switching back at the date of the exit alarm. The results of the described dynamic hedges are presented in Table 4.1.5.

| Year | Annual Returns | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | EMBI Squared Position within would-be FtQ with Static UST Short Position | | | EMBI Squared Position with no UST Exposition within would-be FtQ | | | EMBI Squared Position with UST Long Position within would-be FtQ | | |
| | Transacton Costs: UST (0.00%) EMBI (0.50%) | Transacton Costs: UST (0.00%) EMBI (1.00%) | Transacton Costs: UST (0.00%) EMBI (1.50%) | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) |
| 1998 | 38.62% | 31.33% | 24.37% | 45.05% | 31.25% | 18.69% | 31.15% | 18.67% | 7.31% |
| 1999 | 59.07% | 49.87% | 41.17% | 57.44% | 40.06% | 24.50% | -12.87% | -8.48% | -3.83% |
| 2000 | 19.91% | 11.42% | 3.42% | 14.92% | 0.31% | -12.54% | -17.00% | -15.45% | -13.87% |
| 2001 | 35.66% | 26.03% | 17.02% | 28.95% | 11.99% | -2.84% | 31.85% | 9.27% | -10.08% |
| 2002 | 17.55% | 10.55% | 3.89% | 26.29% | 13.12% | 1.26% | 30.91% | 17.26% | 4.97% |
| 2003 | 31.13% | 27.13% | 23.22% | 30.28% | 22.66% | 15.43% | 28.60% | 21.07% | 13.94% |
| 2004 | 19.48% | 16.41% | 13.39% | 15.33% | 9.97% | 4.84% | 9.79% | 4.70% | -0.20% |
| 2005 | 14.52% | 13.34% | 12.17% | 10.78% | 8.29% | 5.84% | 7.49% | 5.07% | 2.70% |
| 2006 | 9.80% | 8.11% | 6.44% | 6.18% | 2.88% | -0.34% | 3.98% | 0.75% | -2.41% |
| 2007 | -0.97% | -5.75% | -10.33% | 0.16% | -8.27% | -16.04% | 6.98% | -1.95% | -10.18% |
| 2008 | 12.54% | 3.53% | -4.87% | 32.86% | 21.94% | 11.83% | 41.44% | 29.84% | 19.10% |
| 2009 | 34.28% | 27.20% | 20.46% | 31.21% | 17.88% | 5.84% | 40.34% | 26.03% | 13.10% |
| 2010 | 9.35% | 4.25% | -0.65% | 14.07% | 3.95% | -5.33% | 18.50% | 7.98% | -1.66% |

**Table 4.1.5:** Comparison of the dynamic hedges based on the square position in EMBI within would-be Flights-to-Quality.

The respective evolution of the initial 1998 investment of $100 under the discussed hedge strategies is presented in the next Table 4.1.6.

| Year | Portfolio Size (initial investment $100) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | EMBI Squared Position within would-be FtQ with Static UST Short Position | | | EMBI Squared Position with no UST Exposition within would-be FtQ | | | EMBI Squared Position with UST Long Position within would-be FtQ | | |
| | Transacton Costs: UST (0.00%) EMBI (0.50%) | Transacton Costs: UST (0.00%) EMBI (1.00%) | Transacton Costs: UST (0.00%) EMBI (1.50%) | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) |
| 1998 | 138.62 | 131.33 | 124.37 | 145.05 | 131.25 | 118.69 | 131.15 | 118.67 | 107.31 |
| 1999 | 220.50 | 196.83 | 175.57 | 228.37 | 183.82 | 147.76 | 114.27 | 108.61 | 103.20 |
| 2000 | 264.40 | 219.30 | 181.59 | 262.44 | 184.40 | 129.23 | 94.85 | 91.83 | 88.88 |
| 2001 | 358.70 | 276.40 | 212.48 | 338.40 | 206.51 | 125.56 | 125.06 | 100.34 | 79.92 |
| 2002 | 421.65 | 305.56 | 220.76 | 427.35 | 233.61 | 127.15 | 163.72 | 117.66 | 83.89 |
| 2003 | 552.93 | 388.45 | 272.03 | 556.77 | 286.54 | 146.77 | 210.53 | 142.45 | 95.59 |
| 2004 | 660.63 | 452.18 | 308.46 | 642.10 | 315.12 | 153.87 | 231.15 | 149.14 | 95.40 |
| 2005 | 756.57 | 512.51 | 346.00 | 711.29 | 341.24 | 162.86 | 248.45 | 156.71 | 97.97 |
| 2006 | 830.71 | 554.07 | 368.27 | 755.28 | 351.08 | 162.31 | 258.35 | 157.88 | 95.61 |
| 2007 | 822.63 | 522.23 | 330.22 | 756.47 | 322.05 | 136.28 | 276.37 | 154.80 | 85.88 |
| 2008 | 925.81 | 540.65 | 314.13 | 1005.06 | 392.72 | 152.40 | 390.89 | 200.99 | 102.28 |
| 2009 | 1243.14 | 687.68 | 378.41 | 1318.72 | 462.94 | 161.30 | 548.57 | 253.31 | 115.67 |
| 2010 | 1359.38 | 716.90 | 375.95 | 1504.31 | 481.22 | 152.70 | 650.05 | 273.53 | 113.75 |

**Table 4.1.6:** Evolution of the initial investment of $100 over 1998 – 2010 under the dynamic hedges based on the square position in EMBI within would-be Flights-to-Quality.

As could be concluded from Table 4.1.6, the results of the hedge strategy on the right are inferior to the corresponding results of other strategies. This can be attributed to the historically observed existence of the $2^{nd}$ type of Flight-to-Quality, which occurs under the increase in risk-free interest rates, and thus destroys the value if one has a long exposition to the *UST* bonds. So, this strategy is not suitable for the years of economy expansion as it could be verified in Table 4.1.5.

In the next section a few alternative dynamic hedge strategies are analyzed.

## 4.1.7. *EM-UST* Portfolio Dynamically Hedged by Taking Long Positions Only

The dynamic hedge strategy based on the assuming the long positions only, either in *EMBI* or *UST*, can be comprehended as a complete rebalancing of the existing portfolio of *EM* assets, which hence is transformed into the *UST* portfolio of the same size at the date of the entry alarm signal. Later on, at the date of the appearance of the exit signal, the *UST* long portfolio is newly transformed into the *EMBI* long portfolio of the same size. The results of this compete rebalancing strategy, based on switching between *EM* risky and *UST* safe assets are presented in Table 4.1.7 for the analyzed time interval 1998 - 2010.

| Year | Annual Returns: EMBI Long (no Hedge, no Transaction Costs) | Annual Returns under Complete Portfolio Rebalancing within would-be FtQ | | |
|---|---|---|---|---|
| | | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) |
| 1998 | -11.82% | 50.33% | 29.17% | 10.86% |
| 1999 | 24.18% | 46.93% | 23.40% | 3.51% |
| 2000 | 14.41% | 22.14% | -0.48% | -19.04% |
| 2001 | 1.36% | 35.36% | 9.46% | -11.63% |
| 2002 | 13.12% | 35.58% | 14.75% | -3.01% |
| 2003 | 25.66% | 28.32% | 17.16% | 6.89% |
| 2004 | 11.73% | 16.25% | 8.58% | 1.36% |
| 2005 | 10.73% | 12.00% | 7.84% | 3.79% |
| 2006 | 9.88% | 8.42% | 3.60% | -1.04% |
| 2007 | 6.28% | 10.59% | -2.79% | -14.63% |
| 2008 | -10.97% | 41.43% | 24.32% | 9.17% |
| 2009 | 28.26% | 29.27% | 10.23% | -6.11% |
| 2010 | 12.04% | 13.39% | -1.83% | -15.10% |

**Table 4.1.7:** Annual returns under complete rebalancing strategy for diverse transaction costs compared to the EMBI long static portfolio over 1998 - 2010.

The respective evolution of the initial 1998 investment of $100 under the discussed hedge strategy is presented in the next Table 4.1.8.

| Year | Portfolio Size: EMBI Long (no Hedge, no Transaction Costs) | Portfolio Size (initial investment $100) | | |
|---|---|---|---|---|
| | | Transacton Costs: UST (0.25%) EMBI (0.50%) | Transacton Costs: UST (0.50%) EMBI (1.00%) | Transacton Costs: UST (0.75%) EMBI (1.50%) |
| 1998 | 88.18 | 150.33 | 129.17 | 110.86 |
| 1999 | 109.50 | 220.87 | 159.40 | 114.75 |
| 2000 | 125.28 | 269.76 | 158.63 | 92.90 |
| 2001 | 126.98 | 365.13 | 173.62 | 82.09 |
| 2002 | 143.63 | 495.06 | 199.23 | 79.62 |
| 2003 | 180.49 | 635.28 | 233.41 | 85.10 |
| 2004 | 201.66 | 738.49 | 253.43 | 86.26 |
| 2005 | 223.30 | 827.14 | 273.28 | 89.53 |
| 2006 | 245.36 | 896.83 | 283.12 | 88.60 |
| 2007 | 260.75 | 991.84 | 275.24 | 75.63 |
| 2008 | 232.15 | 1402.72 | 342.16 | 82.57 |
| 2009 | 297.75 | 1813.29 | 377.18 | 77.52 |
| 2010 | 333.60 | 2056.12 | 370.29 | 65.82 |

**Table 4.1.8:** Evolution of the initial investment of $100 over 1998 – 2010 under complete rebalancing dynamic hedge strategy compared to the EMBI long static portfolio.

If the results of the complete rebalancing strategy for the most realistic case (with transaction costs for *UST* 0.5% and *EMBI* 1.00%) are compared to the outcomes of the non-hedged *EMBI* long portfolio, see Table 4.1.7, one can conclude that the complete rebalancing strategy annual returns and *EMBI* long annual returns evolve in a opposite to each other manner. Thus, the complete rebalancing investment strategy itself can be considered as a strategy to hedge an *EMBI* long portfolio.

The results of the *EMBI* long portfolio hedged by the complete rebalancing strategy with transaction cost 0.5% for *UST* and 1% for *EMBI* are compared to the outcomes of *EMBI* long static investment and to pure complete rebalancing investment strategy in Table 4.1.9.

| Year | EMBI Long ($100) (no Hedge, no Transaction Costs) | | EMBI Long ($50) Hedged by the Complete Rebalancing Strategy ($50) | | Complete Rebalancing ($100) within would-be FtQ: Transaction Costs 0.5% / 1% | |
|---|---|---|---|---|---|---|
| | Annual Returns | Portfolio Size | Annual Returns | Portfolio Size | Annual Returns | Portfolio Size |
| 1998 | -11.82% | 88.18 | 8.67% | 108.67 | 29.17% | 129.17 |
| 1999 | 24.18% | 109.50 | 23.72% | 134.45 | 23.40% | 159.40 |
| 2000 | 14.41% | 125.28 | 5.58% | 141.95 | -0.48% | 158.63 |
| 2001 | 1.36% | 126.98 | 5.88% | 150.30 | 9.46% | 173.62 |
| 2002 | 13.12% | 143.63 | 14.06% | 171.43 | 14.75% | 199.23 |
| 2003 | 25.66% | 180.49 | 20.72% | 206.95 | 17.16% | 233.41 |
| 2004 | 11.73% | 201.66 | 9.95% | 227.54 | 8.58% | 253.43 |
| 2005 | 10.73% | 223.30 | 9.12% | 248.29 | 7.84% | 273.28 |
| 2006 | 9.88% | 245.36 | 6.42% | 264.24 | 3.60% | 283.12 |
| 2007 | 6.28% | 260.75 | 1.42% | 268.00 | -2.79% | 275.24 |
| 2008 | -10.97% | 232.15 | 7.15% | 287.16 | 24.32% | 342.16 |
| 2009 | 28.26% | 297.75 | 17.52% | 337.47 | 10.23% | 377.18 |
| 2010 | 12.04% | 333.60 | 4.29% | 351.94 | -1.83% | 370.29 |

**Table 4.1.9:** Annual returns and portfolio size evolution for diverse investment strategies.

At a first glance the *EMBI* long investment hedged by the complete rebalancing strategy offers the most consistent year-by-year performance characterized by the lowest volatility. It exhibits the overall portfolio growth above the simple investment in *EMBI*. Although, the overall portfolio growth over 1998 - 2010 of the pure complete rebalancing strategy is superior to the alternatives discussed above, it exhibit three negative yearly results for the years 2000, 2007, and 2010 while the *EMBI* long investment hedged by the complete rebalancing strategy results are positive for all the considered years.

In order to have a better comprehension about investment portfolio dynamics in these three cases, the three charts of annual returns by calendar years are presented in Figure 4.1.9.

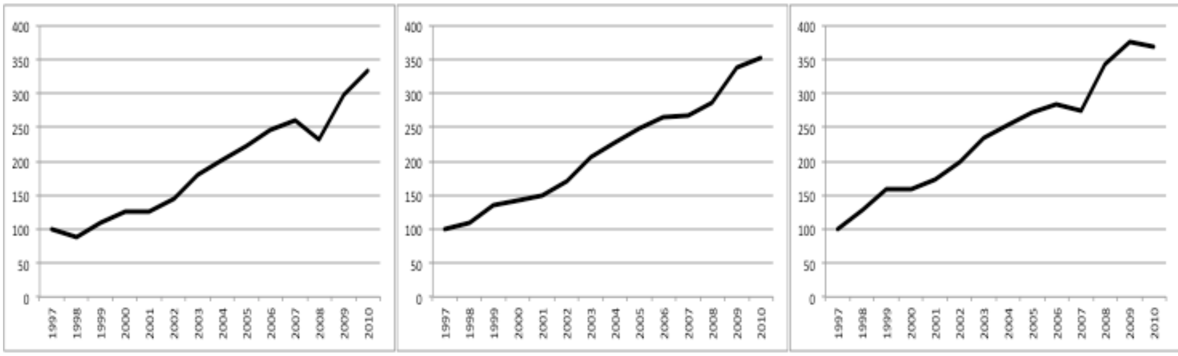



**Figure 4.1.9:** Portfolio evolution for the three investment strategies (from the left to the right: EMBI long investment, EMBI static investment hedged by the complete rebalancing, and the pure complete rebalancing).

The visual analysis of Figure 4.1.9 favors the selection of the middle chart as the less volatile strategy. Nevertheless, in order to prove it more accurately, the charts the rolling annual returns are presented in Figure 4.1.10.

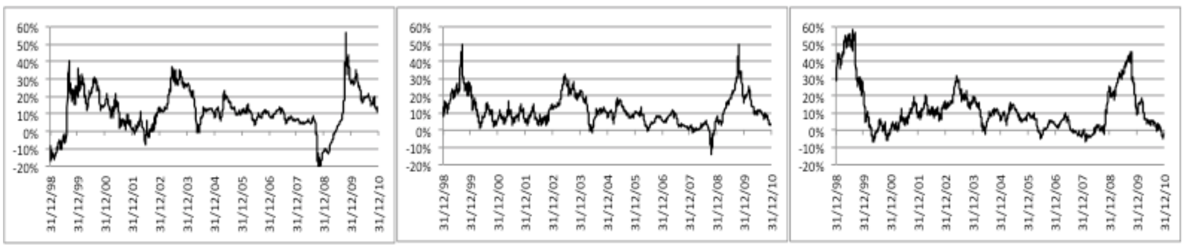



**Figure 4.1.10:** Rolling annual returns for the three investment strategies (from the left to the right: EMBI long investment, EMBI static investment hedged by the complete rebalancing, and the pure complete rebalancing).

From Figure 4.1.10 could be concluded that the major protection against the downside risk in a sense of the rolling annual returns is also provided by the *EMBI* portfolio hedged by the complete rebalancing strategy. The standard deviations of the examined arrays of the rolling annual returns are 11.64%, 8.40%, and 13.39% for the *EMBI* long investment, *EMBI* static investment hedged by the complete rebalancing, and the pure complete rebalancing strategy, respectively.

The next is considered return-to-risk ratio, which is but the observed average return divided by the standard deviation of returns. This is the measure of return to risk trade-off and is used to compare the investment strategies returns. In the case of the three considered investment strategies over 1998 - 2010, their respective return-to-risk ratios are 0.98% for the *EMBI* long investment, 1.35% for the *EMBI* static investment hedged by the complete rebalancing, and 0.90% for the pure complete rebalancing strategy.

This result means that the half *EMBI* long – half complete rebalancing dynamic strategy allows for a much better trade-off between return and risk while compared to the discussed alternatives.

## 4.2. Financial Policies as Responses to Crises and Flights-to-Quality

The final attempt of this work is to address which kind of financial policies could be useful to withstand Flights-to-Quality and major cyclical downturns, ignited by the Flights-to-Quality.

The matter of economic and financial policies is a very old one. For example, in his most influential book, *The General Theory of Employment, Interest, and Money*, written as a response to the Great Depression, the author, John Maynard Keynes (1936), argues that the government could help economy by alternating spending, interest rate and taxes aiming to diminish economic decline in a sense of reducing its magnitude and impact. Keynes (1936) postulated that the government could positively influence the economy targeting its stabilization. In this spirit, he considers economy bottoms, such as recession and depressions, to be issues that require to be resolved as ready as possible with a help of the government intervention. One of the important parts of Keynes's teaching is a necessity to have in place counter-cyclical economic policies, by means of which the government could counteract the excessive lows and the highs in the economic cycle. For example, to overcome economy lows, the government spending could help to recover businesses and accelerate the economy path.

On the other hand during times of blooming prosperity, the government should manage financial markets by increasing interest rates, decreasing government spending, etc. In this way, the government policies would counterbalance economic highs and lows, without any aspiration to transform each into another, but just stabilizing economy and financial markets.

It is important to understand how appropriate financial policies could improve stability of financial markets, against Flights-to-Quality and alike events. These episodes are nothing but revelations of risk-on/risk-off behavior. At the ignition of crises/ Flights-to-Quality markets increasingly focus on global systemic issues related to abruptly growing risk aversion. In its turn, the termination of a Flight-to-Quality evidences that markets are newly back to analyzing idiosyncratic conditions of countries, industries, regions, etc., instead of being worried about globalized features.

In this context the *UST* bonds play an important role as an object of highly elevated demand within the risk-off phases or Flights-to-Quality. For example, according to DeLong (2010), it is not unusual for prices of such safe haven securities to jump by more than 15% a month in times of growing risk aversion and search for safety as it was the case in May 2010, when the yield of UST bonds with a 30-year maturity dropped 50 basis points within a month.

A fact like this can already be considered as a remarkable signal of a shift in a relative demand for quality of safe haven instruments. Additionally, the initiated in 2007 fall in the yields of *UST* bonds continued through 2010 – 2012, confirms that in times of global instabilities (Subprime crisis, Global Financial turmoil of 2008-2009, Greece, Ireland, and Portugal debt worries, Eurozone structural deficiencies, a possibility of China hard landing, among others) the demand for safe and quality assets is getting stronger.

This excessively high relative demand for safe assets has the two following components. On one hand it could be primarily originated out of sharp increases in risk aversion. Under these conditions, a Flight-to-Quality is rather a Flight-from-Risk. In the previous Chapter such events (with a primarily cause related to the risk attitudes) are described as risk asset appetite driven events or expectation driven events.

On the other hand the excessively high relative demand for safe assets could be rather caused by a decrease in supply of such assets. The Flights-to-Quality, happening under such scenarios, are rather Flights-toward-Safe-Assets. In the previous Chapter such events (with a primarily cause related to a search for a safe haven instruments) are considered as *UST*-driven events whose causes are related to the insufficient supply. In the first place the counterbalancing policy actions responding to the *UST*-driven events are discussed.

### 4.2.1. Policies on the Supply Side of the Safe Assets Supply-Demand Misbalances

As examples of situations, characterized by the insufficient supply, it is possible to mention a change in a status of government bonds of European periphery. Prior to the Eurozone debt crisis, these bonds by a vast majority of investors were considered to be safe assets. As of the beginning of 2012, they have lost such a status, causing in this indirect way an increase in the *UST* bond prices.

Of course, the contemporary world is financially entangled and interdependent. The "excessive" increases in prices of safe assets make them even more attractive for investors while compared to the risky, for example *EM* securities. Thus, the investors, who otherwise would be satisfied with risk/return features of these risky investments, begin to newly reexamine their investment in a light of quite attractive return possibilities due to the increases in prices of safe assets, and eventually fly to the quality and safety of such assets while accompanied by reasonable returns.

Thus, if the creditworthy governments around the world could and would augment supply of safe assets, the prices of such assets would be caused to decline, and consequently, the potential strength of Flights-to-Quality and crises would be reduced. It means that there would be less capital outflows from the productive emerging economies and from the risky real economy sectors of the developed geographies to the U.S., German, and other alike government custodies. This is likely to augment the global welfare of the world. Of course, there should be no pretention, as in hedge strategies based on dynamic switching, to transform economic downturns into upturns. But still there seem to be a considerable space for reducing financial instability and smoothing lows and highs of economy course.

If there would be in place a trustworthy Alarm Signal System, similar to the proposed in the previous Chapter, whose warnings would be considered as valuable by the government capable of supplying safe assets to the market, there would be a possibility of a timely action in order to reduce excess demand for safe haven assets.

In general, efficient markets tell market participants what is currently valuable, giving them a signal to produce more of these goods, to offer more of these services, etc. In other words, the invisible hand of the efficient markets would be capable of resolving a problem of excess demand for any goods supplied by the market. However the situation concerning a supply of safe assets is different, as this type of assets is not produced by a free market but rather by a social planner, i.e. government resource-planning mechanism. So the governments, whose creditworthiness still remains not damaged in perception of market participants, should create a lot more of safe assets in times of coming and/or developing occurrences of Flights-to-Quality and crises in order to respond to the signals given by the markets.

Another issue is related to the form of such governments´ reaction. Diverse approaches could be undertaken in response to or anticipating those sharp increases in demand for safe assets (i.e. Flights-to-Quality). For example, the creditworthy governments could start guaranteeing the debt of private entities, transforming, in this way, risky assets into the safe ones. Additionally, the state governments of the developed countries could start borrowing, and utilize that borrowed money to acquire some of the risky assets, especially subjects to developing sell-offs, given a fair quality of such assets.

As there is not enough research and data regarding which kind of such interventions would be the most effective, and also due to the practical inexistence of such attempts, the creditworthy governments should discover the most efficient way to dry out an excess demand for safe assets by trial and error experience.

Thus the Alarm Signal System could be of a great utility should the governments start thinking about equilibrating supply and demand for safe assets.

### 4.2.2. Policies on the Demand Side of the Risky Assets Supply-Demand Misbalances

Policy approaches for the less developed and/or smaller economies aiming at minimizing their susceptibility to financial crises are thoroughly addressed by Pettis (2001). He argues that certain crises like the Asian and Latin American crises at the end of the last century were caused by the bad management of the sovereign balance sheet and not by the economic mismanagement. Pettis (2001) argues that these emerging market financial crises were related to the inadequate liability management at the local country level.

Author also defends that one of the most important reasons allowing for occurrences of crisis situations in emerging markets, is that emerging market investors have been underestimating the source and the magnitude of volatility in emerging financial markets. This volatility is related to the reevaluation of the risk-return profile, in a first place, by the international investors. Thus, the positive news regarding the *EM* local economies, in principle, could help investors to alter their judgments. So, the timeliness of the appropriate positive news is very important.

It is where a trustable Alarm Signal System warning of approaching financial stresses (Flights-to-Quality, crises, etc.) comes to a stage of the local policies of the emerging market countries. For example, structured communications on the improvement of the management of the liabilities side of a country balance sheet could be released. News regarding a possible diversification of the funding sources could be also very welcome at times of distress and turmoil. Eventually, debt auctions could be postponed for a while to be held in a better financial environment after a termination of the predicted Flights-to-Quality.

Caballero and Curlat (2008) emphasize that in times of economic crises the right timing for appropriate government policy decisions may diminish unfavorable consequences of financial turmoil on the real economy. Thus, the proposed Alarm Signal System could be considered an “early bird” in a future “flock” of alarm systems aimed at accurate forecasting of the probable financial disasters, which opens a way to the improving financial stability, so needed in our times.

# 5. Conclusions

This research investigates the impact of Flight-to-Quality on the performance of financial markets, in particular, and economic conditions, in general. This important phenomenon is analyzed from the point of view of the origins of financial instability, as potentially each such event could result in a financial crisis if not properly and timely addressed.

This work contributes to the efforts focused on achieving less volatile financial environment. After the thorough survey of the state of the art, it presents the systematic identification, phenomenological description and model analysis of the Flights-to-Quality out of Emerging Markets towards U.S. Treasury debt issues, occurring over the 1998-2010 period.

The importance of the subject of this research has been growing during its progress due to the two following reasons. First, within its time frame, the Global Economic crisis and the Credit Crunch, the strongest of the Flights-to-Quality, occurred. Thus, an improved comprehension of their nature and revelation of the origins of preceding events has become highly important and desirable. Second, the Emerging Markets' influence on the global economy is already a well-established feature of the contemporary financial environment.

This research represents the attempt to address in depth the nature of Flight-to-Quality events and the problem of their forecasting. First of all, in order to define the array of the events analyzed in this study, an automated identification algorithm has been developed, based on the analysis of the comparative total returns dynamics of the chosen baskets of risky and safe assets. In this work the model of the investment universe is proposed, which consists of the two sub-universes: safe and risky asset domains. This model allows elaboration of an Alarm Signal System to warn of upcoming events. Further on, an applicability of the developed Alarm Signal System to the interest rate risk management is assessed by testing historical performance of diverse hedge strategies based on the outcomes of the proposed Alarm Signal System. Additionally, this System is found to be a potentially important tool for the improvement of timeliness of financial policies needed as responses to periods of financial turmoil.

A systematic description of Flight-to-Quality origins and the consecutive delimiting of time frames of these events on an *ex-ante* basis are made possible due to the following contributions produced during this research.

First is the elaboration of the working definition of a Flight-to-Quality. It is given in terms of total returns, which is the metrics, the most suitable for measuring a comparative performance of different assets. This definition is applicable to diverse asset classes and it is not restricted only to the fixed income origination-destination pairs of assets, mutually affected during Flight-to-Quality episodes. Even for the debt instruments, the approach based on the individual performance of each of the asset classes is more precise in respect to commonly employed differential spread techniques, as it preserves information of the individual dynamics and not only the comparative one. Additionally, the definition in terms of the total returns is compatible with the newly proposed typology of Flight-to-Quality events.

The second advance of this work is the detailed typological description of Flight-to-Quality events, given in the form of a matrix. As a primary scale of this matrix, the sign of the risk-free interest rate changes is used. In turn, for the case of decreasing risk-free interest rates, a secondary dimension is employed. This takes into account the sign of the changes in the interest rate of the risky assets. In this manner, it is possible to distinguish the two most general types of Flight-to-Quality. The first type, which is the most common for turning points and crisis phases, leads to an increase in total returns of the safe assets. On the other hand, the second type, which is rather rare (being observed amidst improving economic conditions), is accompanied by a decrease in the safe asset performance due to the expansion of the overall economic activity. The first-type Flight-to-Quality events are then segregated into the two sub-types. The *1.A-subtype* phenomena, with decaying total returns of the risky assets, are the most frequent episodes under a slowdown of the economy.

The important insight of this research is the attribution of the *1.B-subtype* phenomena, characterized by the increase in total returns of both safe and risky assets, to the initial worries of investors in respect to the future changes in the course of the economy. Therefore, these events can be interpreted as indicators of upcoming turning points in general, and in particular as warnings of an approaching slowdown.

Additionally, all the types and sub-types of Flights-to-Quality are put in the context of the economic environment. This is obtained by super-positioning these phenomena over the curves depicting the U.S. and the World *GDP* growth rates over the analyzed time interval 1998 – 2010. This study proves a validity of the interpretation given above to diverse types and sub-types of Flight-to-Quality.

The third contribution of this research is the development of the automated identification algorithm, which is applied on *ex-post* basis to detect precise time frames of the historically observed Flight-to-Quality phenomena. This identification algorithm is based on the comparative analysis of the total returns of the safe and risky asset classes. The identification approach developed here represents an important step as it gives a new insight into the analysis of circumstances under which Flights-to-Quality occur, allowing automatic detection of the initial and final dates of the studied episodes. The identification algorithm developed for a general case is applied to *EMBI* and *ITRROV* index series in order to detect the periods when investment flies out of Emerging Market securities towards U.S. Treasury bonds within 1998 – 2010. These empiric results are used further on for the analyses of the accuracy of the Alarm Signal System, which is the next outcome of this research allowing for delimiting Flights-to-Quality on before the event basis.

The fourth contributing aspect of this work is a setting up of the Model of Flight-to-Quality, which represents a foundation for the aforementioned Alarm Signal System. This Model is based on the assumption that the underlying investment universe consists of safe and risky asset sub-universes. The analysis of its main value drivers, such as a risk-free interest rate and risk premium, allows for a quantification of the investors´ appetites towards safe and risky securities as well as the cumulative asset appetite for the totality of the two considered types of investment instruments existing in the modeled investment universe.

The three asset appetite metrics, for risky, safe, and cumulative appetites, originate from the respective index performances using the two special procedures, namely, the correction for the risk-free interest rate induced effects and the adjustment of the indexes´ returns to the targeted level of the expected riskiness, being the same for the asset classes under investigation. The latter adjustment procedure is important in the sense that it allows the returns of the diverse assets classes to be brought to the same level of the expected riskiness, hence making them comparable.

This is an insightful result as the proposed asset appetite metrics allows for the quantitative analyses of investors´ willingness to hold safe assets in comparison to risky securities, which is important for Flight-to-Quality comprehension. The proposed Model of Flight-to-Quality is applied to the quantification of the investors´ appetites towards safe U.S. Treasury bonds and risky Emerging Market debt securities within the period 1998 – 2010.

The fifth point is the development of the Alarm Signal System to warn of the start and termination dates of Flight-to-Quality events. The set of rules allowing for the generation of the alarm signal are based on the comparative analyses of the assets appetite dynamics. The proposed assets appetite metrics, being a fundamental part of the Alarm Signal System, allows delimiting of Flight-to-Quality ignitions and terminations on an *ex-ante* basis.

An efficiency analysis of the Alarm Signal System is also performed. Under this exercise the Alarm Signal System is applied to delimiting the Flight-to-Quality windows on an *ex-ante* basis; the data from the *EMBI* and *ITRROV* indexes within 1998 – 2010 are employed. Such delimited time windows correspond to hypothetical would-be Flights-to-Quality out of Emerging Market securities towards U.S. Treasury bonds. Being compared to the Flights-to-Quality diagnosed on an *ex-post* basis by the developed automated total return-based identification algorithm, the efficiency analyses of the proposed Alarm Signal System certify its applicability to delimiting Flight-to-Quality start and termination dates. It is worth mentioning that the proper study of the termination dates of the Flight-to-Quality by itself can be considered an advance in the investigation of these episodes.

The efficiency ratio of the Alarm Signal System, measured as the ratio of the total strength of the Flights-to-Quality delimited on an *ex-ante* basis over the cumulative impact of the historically occurred Flights-to-Quality, both expressed in terms of total return differences, is found to be above 75%. This means that potentially the three quarters of the adverse impacts of Flights-to-Quality can be avoided by the appropriate interest rate risk management techniques.

The sixth accomplishment is the application of the Alarm Signal System for engineering diverse dynamic hedge strategies. Several dynamic interest rate hedge strategies, based on the Alarm Signal System, while compared to the static ones, prove the usefulness of the proposed approach. The hypothetical hedges with no transaction costs are discussed in order to explain the underlying mechanisms, while the posterior introduction of the transaction costs allows for the more realistic assessment of the proposed hedge strategies. They are analyzed in terms of standard deviations and risk-to-return ratios. For the investigated time interval 1998 – 2010 the most prominent strategy is found to be the long position in *EMBI* hedged by the pair of *EMBI-ITRROV* exposure dynamically switched within the would-be Flight-to-Quality windows. This is especially attractive as it permits to avoid the downside risks and results in positive returns for any calendar year.

Finally, the seventh contribution, the generated alarm signals are considered to be potentially useful for the correct choice of the respective financial policy to be implemented in accordance with the prevailing level of investors´ willingness to invest, described by the assets appetite metrics. Additionally, the discussion of financial policies and their timeliness was addressed from the point of view of supply-demand misbalance both in respect to the safe and the risky assets sides representing an advance in this issue too.

This conclusion section is finalized by the indication of the possible future paths emerging as a continuation of the present research. There are many of them. First of all, instead of the Emerging Market debt, the Flights-to-Quality out of stocks of emerging economies could be considered, as well as many other origination-destination pairs of assets. Another future advance of the methodology is related to the most complex situations involving three and more asset classes, in order to bring this approach closer to the complex reality of the current economic environment. The quantitative optimization of the suggested approach can be performed by each of the parameters used in the presented approach. Additionally along with Flights-to-Quality, the opposite events of "anti-Flights-to-Quality" or periods of the extreme outperformance of risky assets over the safe assets could be addressed. This is especially important for the periods when all asset classes become correlated with each other and all the financial markets are functioning in the Risk-on-Risk-off switching mode. In a certain sense, this is modeled while developing dynamic hedge strategies. This work itself presents multiple horizons for future developments. The initial discussion addressing the timeliness of politics targeting better financial and economic stability deserves to be continued in the follow-up of the present research.

# References


Abreu, D. and Brunnermeier, M. (2003), Bubbles and Crashes. *Econometrica* **71**(1), 173-204.

Ahn, H. and Kim, K. (2009), Bankruptcy Prediction Modeling With Hybrid Case-Based Reasoning and Genetic Algorithms Approach. *Applied Soft Computing* **9**(2), 599-607.

Albanese, C., Jackson, K., and Wiberg, P. (2004), A New Fourier Transform Algorithm for Value at Risk. *Quantitative Finance* **4**, 328-338.

Alfaro, R., Garcia, F., and Jara, A. (2004), Bank Lending Channel and the Monetary Transmission Mechanism: The Case of Chile. *Working Paper 223. Central Bank of Chile*.

Allen, F. and Gale, D. (1998), Optimal Financial Crises. *Journal of Finance* **53**(4), 1245-1284.

Allen, F. and Gale, D. (2000a), Financial Contagion. *Journal of Political Economy* **108**(1), 1-33.

Allen, F. and Gale, D. (2000b), Bubbles and Crises. *Economic Journal* **110**(460), 236-255.

Allen, F. and Gale, D. (2004), Financial Intermediaries and Markets. *Econometrica* **72**(4), 1023-1061.

Allen, F. and Gale, D. (2007), *Understanding Financial Crises*. Oxford: Oxford University Press.

Allen, F. and Gorton, G. (1993), Churning Bubbles. *Review of Economic Studies* **60**(4), 813-836.

Allen, F., Babus, A., and Carletti, E. (2009), Financial Crises: Theory and Evidence. *Annual Review of Financial Economics* **1**(1), 97-116.

Allen, F., Morris, S., and Postlewaite, A. (1993), Finite Bubbles with Short Sale Constraints and Asymmetric Information. *Journal of Economic Theory* **61**(2), 206-229.

Alonso, I. (1996), On Avoiding Bank Runs. *Journal of Monetary Economics* **37**(1), 73-87.

Alpert, M. and H. Raiffa (1982), A Progress Report on the Training of Probability Assessors. In: Kahneman, D., Slovic, P., and Tversky, A., (Ed.) *Judgment Under Uncertainty: Heuristics and Biases*, pp. 294-305. Cambridge: Cambridge University Press.

Altman, E. (1968), Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance* **23**(4), 589-609.

Altman, E., Haldeman, R., and Narayanan, P. (1977), ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations. *Journal of Banking and Finance* **1**(1), 29-54.

Amir, E. and Ganzach, Y. (1998), Overreaction and Underreaction in Analysts Forecast. *Journal of Economic Behavior and Organization* **37**(3), 333-347.

Andolfatto, D. and Nosal, E. (2006), Moral Hazard in the Diamond-Dybvig Model of Banking. *Working Paper 06-23*. *The Federal Reserve Bank of Cleveland*.

Andriani, P. and McKelvey, B. (2007), Beyond Gaussian Averages: Redirecting International Business and Management Research toward Extreme Events and Power Laws. *Journal of International Business Studies* **38**(7), 1212–1230.

Arora, V. and Cerisola, M. (2002), How Does U.S. Monetary Policy Influence Sovereign Spreads in Emerging Markets? *IMF Staff Papers* **48**(3), 474-498.

Arrow, K. (1953), The Role of Securities in the Optimal Allocation of Risk–Bearing. *Econometrie*; as translated and reprinted in 1964, *Review of Financial Studies* **31**, 91-96.

Arrow, K. (1965), *The Theory of Risk Aversion*. Helsinki: Yrjo Jahnssonin Foundation.

Ausloos, M. and Ivanova, K. (2001), *Crashes: Symptoms, Diagnoses and Remedies*. Berlin: Springer Verlag.

Baesel, J. (1974), On the Assessment of Risk: Some Further Considerations. *The Journal of Finance* **29**(5), 1491-1494.

Ball, P. (2006), Econophysics: Culture Crash. *Nature* **441**(7094), 686–688.

Balsam, S. and Kim, S. (2001), Effects of Interest Rate Swaps. *Journal of Economics and Business* **53**(6), 547-562.

Balzer, L. (2001), Investment Risk: a Unified Approach to Upside and Downside Returns. In: Sortino, F. and Satchell, S., (Ed.) *Managing Downside Risk in Financial Markets: Theory, Practice and Implimentation*, pp. 103-155. Oxford: Reed Educational and Professional Publishing Ltd.

Barber, B. and Odean, T. (2001), Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment. *The Quarterly Journal of Economics* **116**(1), 261-292.

Barberis, N. and Thaler R. (2003), A Survey on Behavioral Finance. In: Constantinides, G., Harris, M. and Stulz, R., (Ed.) *Handbook of the Economics of Finance*, pp. 1051-1121. North-Holland, Amsterdam: Elsevier Science B.V.

Barth, J., Li, T., and Phumiwasana, T. (2009), *The U.S. Financial Crisis: Credit Crunch and Yield Spreads*. RBS Reserve Management Trends 2009. London: Central Banking Publications Ltd.

Baum, J. and McKelvey, B. (2006), Analysis of Extremes in Management Studies. *Research Methodology in Strategy and Management* **3**, 123–196.

Baur, D. and Lucey, B. (2009), Flights and Contagion - An Empirical Analysis of Stock-Bond Correlations. *Journal of Financial Stability* **5**(4), 339-352.

Bawa, V. (1975), Optimal Rules For Ordering Uncertain Prospects. *Journal of Financial Economics* **2**(1), 95-121.

Beber, A., Brandt, M., and Kavajecz, K. (2009), Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market. *Review of Financial Studies* **22**(3), 925-957.

Becker, R., Enders, W. and Hurn, S. (2006), Modeling Inflation and Money Demand Using a Fourier-Series Approximation. In: Milas, C., Rothman, P., and Elsevier, D., (Ed.) *Nonlinear Time Series Analysis of Business Cycles*, pp. 221-244, Amsterdam: Elsevier.

Bekaert, G., Harvey, C, and Ng, A. (2005), Market Integration and Contagion. *Journal of Business* **78**(1), 39-70.

Bernadell C., Coche, J., and Nyholm, K. (2005), Yield Curve Prediction for the Strategic Investor. *Working Paper 472. European Central Bank.*

Bernanke, B., Gertler, M., and Gilchrist, S. (1996), The Financial Accelerator and the Flight-to-Quality. *The Review of Economics and Statistics* **78**(1), 1-15.

Bicksler, J. and Chen, A. (1986), An Economic Analysis of Interest Rate Swaps. *The Journal of Finance* **41**(3), 645-655.

Black F. (1972), Capital Market Equilibrium with Restricted Borrowing. *Journal of Business* **45**(3), 444-454.

Black F. and Scholes M. (1973), The Pricing of Options and Corporate Liabilities. *Journal of Political Economy* **81**(3), 637-659.

Black, F. (1976), The Pricing of Commodity Contracts. *Journal of Financial Economics* **3**, 167-179.

Black, F. (1987), *Business Cycles and Equilibrium*. Cambridge: Basil Blackwell.

Black, F. (1995), *Exploring General Equilibrium*. Cambridge: MIT Press.

Blinder, A. and Zandi, M. (2010), How the Great Recession Was Brought to an End. *Working Paper. Princeton University*.

Bloom, D., Mackel, P., Williams, S., McDonald, M., and Austin, M. (2011), Why News Flow Dominates. *Macro Currency Strategy HSBC Global Research*, 7-10.

Blume, M. (1971), On the Assessment of Risk. *The Journal of Finance* **26**(1), 1-10.

Borio, C. and Drehmann, M. (2009), Assessing the Risk of Banking Crises – Revisited. *Bank for International Settlements Quarterly Review* **1**, 29-46.

Borio, C. and Lowe, P. (2002), Assessing the Risk of Banking Crises. *Bank for International Settlements Quarterly Review* **4**, 43-54.

Boyacioglu, M, Kara, Y., and Baykan, O. (2008), Predicting Bank Financial Failures Using Neural Net-Works, Support Vector Machines and Multivariate Statistical Methods: A Comparative Analysis in the Sample of Savings Deposit Insurance Fund (SDIF) Transferred Banks in Turkey. *Expert Systems with Applications* **36**(2), 3355–3366.

Boz, E. (2007), Can Miracles Lead to Crises? The Role of Optimism in Emerging Markets Crises. *Working Paper 223. International Monetary Fund*.

Bradley, B. and Taqqu, M. (2005), Empirical Evidence on Spatial Contagion Between Financial Markets. *Finance Letters* **3**(1), 77-86.

Brealey, R., Myers, S., and Allen, F. (2007), *Principle of Corporate Finance*. 9th edn, New York: McGraw-Hill.

Breeden, D. (1979), An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities. *Journal of Financial Economics* **7**(3), 265-296.

Brennan, M. (1993), Agency and asset pricing. *Working Paper 6-93. UCLA-Anderson Graduate School of Management*.

Briere, M., Chapelle, A., and Szafarz, A. (2008), No Contagion, Only Globalization and Flight-to-Quality. *Working Paper 08-22.RS.Universite Libre de Bruxelles*.

Brocato, J. and Kenneth, S. (2010), Sudden Equity Price Declines and the Flight-to-Safety Phenomenon: Additional Evidence Using Daily Data. *Journal of Economics and Finance*, 1-16.

Brock, W. and Mansky, C. (2011), Competitive Lending with Partial Knowledge of Loan Repayment: Some Positive and Normative Analysis. *Journal of Money, Credit and Banking* **43**(2-3), 441–459.

Broner, F., Gelos, G., and Carmen R. (2006), When in Peril, Retrench: Testing the Portfolio Channel of Contagion. *Journal of International Economics* **69**(1), 203-230.

Bruner, R., Eades, K., Harris, R., and Higgins, R. (1998), Best Practices in Estimating the Cost of Capital: Survey and Synthesis. *Financial Practice and Education* **8**(1), 13-28.

Brunnermeier, M. (2009), Deciphering the Liquidity and Credit Crunch 2007-08. *Journal of Economic Perspectives* **23**(1), 77-100.

Brunnermeier, M. and Nagel, S. (2004), Hedge Funds and the Technology Bubble. *Journal of Finance* **59**(5), 2013-2040.

Brunnermeier, M. and Pederson, L. (2005), Predatory trading. *Journal of Finance* **60**(4), 1825-1863.

Brunnermeier, M. and Pederson, L. (2009), Market Liquidity and Funding Liquidity. *Review of Financial Studies* **22**(6), 2201-2238.

Bryant, J. (1980), A Model of Reserves, Bank Runs, and Deposit Insurance. *Journal of Banking and Finance* **4**(4), 335–344.

Bunda, I., Hammann, J., and Lall, S. (2010), Correlations in Emerging Market Bonds: The Role of Local and Global Factors. *Working Paper 10/6. International Monetary Fund.*

Bustillo, I. and Velloso, H. (2002), United States Interest Rates, Latin American Debt and Financial Contagion. *CEPAL Review* **78**, 83-99.

Butikofer, J. (2010), *Emerging Markets Bonds*. Luxembourg: Union Bancaire Privée.

Caballero, R. and Krishnamurthy, A. (2008), Collective Risk Management in a Flight-to-Quality Episode. *Journal of Finance* **63**(5), 2195-2230.

Caballero, R. and Krishnamurthy, A. (2009), Global Imbalances and Financial Fragility. *American Economic Review* **99**(2), 584-588.

Caballero, R. and Kurlat, P. (2008), Flight-to-Quality and Bailouts: Policy Remarks and a Literature Review. *Working paper 08-21. MIT Department of Economics*.

Calomiris, C. and Gorton, G. (1991), The Origins of Banking Panics: Models, Facts, and Bank Regulation. In: Hubbard, G., (Ed.) *Financial Markets and Financial Crises*, pp. 107-173. Chicago: University of Chicago Press.

Calomiris, C. and Mason, J. (2003), Fundamentals, Panics, and Bank Distress During the Depression. *American Economic Review* **93**(5), 1615–1647.

Calvet, L. and Fisher, A. (2002), Multifractality in Asset Returns: Theory and Evidence. *Review of Economics and Statistics* **84**(3), 381-406.

Calvo, A. (1988), Servicing the Public Debt: the Role of Expectations. *The American Economic. Review* **78**(4), 647-661.

Calvo, G., Leiderman, L., and Reinhart, C. (1996), Inflows of Capital to Developing Countries in the 1990s'. *Journal of Economic Perspectives* **10**(2), 123-139.

Carey, M., Prowse, S., Rea, J., and Udell, G. (1993), The Economics of the Private Placement Market. *Staff Studies 166. Board of Governors of the Federal Reserve System (U.S.)*.

Carlin, B., Lobo, M., and Viswanathan, S. (2007), Episodic Liquidity Crises: Cooperative and Predatory Trading. *Journal of Finance* **62**(5), 2235-2274.

Carlson, M. (2002), Causes of bank suspensions in the panic of 1893. *Working Paper 2002-11. Board of governors – Federal Reserve System (U.S.)*.

Castiglionesi, F. and Navarro, N. (2007), Optimal Fragile Financial Networks. *Discussion paper 2007-100. Tilburg University*.

Cavalcanti, R. (2010), Inside-Money Theory after Diamond and Dybvig. *Federal Reserve Bank of Richmond Economic Quarterly* **96**(1), 59-82.

Cerny, A. (2003), The Risk of Optimal, Continuously Rebalanced Hedging Strategies and it's Efficient Evaluation via Fourier Transform. *Working Paper. The Cass Business School*.

Chambers, D., Carleton,W., and McEnally, R. (1988), Immunizing Default-Free Bond Portfolios with a Duration Vector. *Journal of Financial and Quantitative Analysis* **23**(1), 89–104.

Chambers, S. (1934), Fluctuations in Capital and the Demand for Money. *Review of Economic Studies* **2**(1), 38-50.

Champ, B., Smith, B., and Williamson, S. (1996), Currency Elasticity and Banking Panics: Theory and Evidence. *Canadian Journal of Economics* **29**, 828-864.

Chance, D. and Brooks, R. (2010), *Introduction to Derivatives and Risk Management*. 8th edn, Mason, OH: Cengage Learning.

Chance, M. (1983), Floating Rate Notes and Immunization. *Journal of Financial and Quantitative Analysis* **18**(3), 365-380.

Chang, R. and Majnoni, G. (2001), International Contagion: Implications for Policy. In: Claessens, S. and Forbes, K., (Ed.) *International Financial Contagion*, pp. 407-430. Boston: Kluwer Academic Publishers.

Chang, R. and Velasco, A. (2001), A Model of Financial Crises in Emerging Markets. *The Quarterly Journal of Economics* **116**(2), 489-517.

Chari, V. and Jagannathan, R. (1988), Banking Panics, Information, and Rational Expectations Equilibrium, *Journal of Finance* **43**(3), 749-760.

Chen. W. and Shih, J. (2006), A Study of Taiwan's Issuer Credit Rating Systems Using Support Vector Machines. *Expert Systems with Applications* **30**(3), 427-435.

Chou, J., Chang, C., and Chen, C. (2009), The Use of Term Structure Information in the Hedging of Japanese Government Bonds. *The International Journal of Business and Finance Research* **3**(2), 131-146.

Clark, J. (1899), The *Distribution of Wealth: A Theory of Wages, Interest and Profits*. New York: The Macmillan Company.

Clements M., Hans, F., and Swanson, N. (2004), Forecasting Economic and Financial Time Series Using Nonlinear Methods. *International Journal of Forecasting* **20**(2), 169-183.

Cochrane, J. (2001), *Asset Pricing*. Princeton, N.J.: Princeton University Press.

Connolly, H. and Taylor D. (1984), The Exact Timing of the Collapse of an Exchange Rate Regime and its Impact on the Relative Price of Traded Goods. *Journal of Money, Credit and Banking* **16**(2), 194-207.

Corsetti, G., Pericoli, M., and Sbracia, M. (2005), Some Contagion, Some Interdependence: More Pitfalls in Tests of Financial Contagion. *Journal of International Money and Finance* **24**(8), 1177-1199.

Corsetti, G., Pesenti, P., and Tille, C. (2000), Competitive Devaluations: Toward a Welfare-Based Approach. *Journal of International Economics* **51**(1), 217-241.

Coudert, V. and Gex, M. (2006), Can Risk Aversion Indicators Anticipate Financial Crises? *Financial Stability Review* **9**, 67-87.

Coudert, V., and Gex, M. (2007) Does Risk Aversion Drive Financial Crises? Testing the Predictive Power of Empirical Indicators. *Working Paper 2007-02. Centre d'Etudes Prospectives et d'Informations Internationales*.

Cowen, T. (2009), A Simple Theory of the Financial Crisis; or, Why Fischer Black still matters. *Financial Analysts Journal* **65**(3), 17-20.

Cox, J., Ingersoll, J., and Ross, S. (1979), Duration and Measurement of Basis Risk. *Journal of Business* **52**(1), 389-403.

Cox, J., Ingersoll, J., and Ross, S. (1985), A Theory of the Term Structure of Interest Rates. *Econometrica* **53**(2), 385–407.

Dages, G., Palmer, D., and Turney, S. (2005), An Overview of the Emerging Market Credit Derivatives Market. *Working Paper. Federal Reserve Bank of New York*.

Dalio, R. (2005), *Engineering targeted returns and risks*. Westport: Bridgewater Associates.

Davis, P. and Karim, D. (2008), Comparing Early Warning Systems for Banking Crises. *Journal of Financial Stability* **4**(2), 89-120.

De Long, J., Shleifer, A., Summers, L., and R. Waldmann, R. (1990), Noise trader risk in financial markets. *Journal of Political Economy* **98**(4), 703−738.

Debreu, G. (1959), *Theory of Value: An Axiomatic Analysis of Economic Equilibrium*. New Haven: Yale University Press.

Dell'Ariccia, G., Detragiache, E., and Rajan, R. (2008), The Real Effects of Banking Crises. *Journal of Financial Intermediation* **17**(1), 89-112.

Dellinger, J. (2006), *The Handbook of Variable Income Annuities*. Hoboken, New Jersey: John Willey & Sons.

DeLong, J. (2010), *The Flight-to-Quality*. New York: Project Syndicate.

Demirguc-Kunt, A. and Detragiache, E. (2005), Cross-Country Empirical Studies of Systemic Bank Distress: A Survey. *Working Paper 96/05. International Monetary Fund*.

Demirguc-Kunt, A., Detragiache, E., and Gupta, P. (2006), Inside the Crisis: An Empirical Analysis of Banking Systems in Distress. *Journal of International Money and Finance* **25**(5), 702-718.

Demyanyk, Y. and Hasan, I. (2009), Financial Crises and Bank Failures: A Review of Prediction Methods. *Working Paper 09-04. Federal Reserve Bank of Cleveland.*

Dhankar, R. and Singh, R. (2005), Arbitrage Pricing Theory and the Capital Asset Pricing Model: Evidence from the Indian Stock Market. *Journal of Financial Management and Analysis* **18**(1), 14-27.

Diamond, D. and Dybvig, P. (1983), Bank Runs, Liquidity and Deposit Insurance. *Journal of Political Economy* **91**(3), 401-419.

Diamond, D. and Rajan, R. (2001), Liquidity Risk, Liquidity Creation and Financial Fragility: A Theory of Banking. *Journal of Political Economy* **109**(2), 287-327.

Diamond, D. and Rajan, R. (2005), Liquidity Shortage and Banking Crises. *The Journal of Finance* **60**(2), 615-647.

Diebold, F. and Li, C. (2006), Forecasting the Term Structure of Government Bond Yields. *Journal of Econometrics* **130**(2), 337-364.

Diebold, F. and Rudebusch, G. (1989), Scoring the Leading Indicators. *Journal of Business* **62**(3), 369-391.

Diebold, F., Ji, L., and Li, C. (2006), A Three-Factor Yield Curve Model: Non-Affine Structure, Systematic Risk Sources, and Generalized Duration. In: Klein, L., (Ed.) *Long-Run Growth and Short-Run Stabilization: Essays in Memory of Albert Ando*, pp. 240-274. Cheltenham, U.K.: Edward Elgar.

Dooley M. (2000), A Model of Crises in Emerging Markets. *The Economic Journal* **110**(460), 256-272.

Dordain, J., Mayrargue, S., and Patry, C. (2003), *Robust Rho Hedging*. Dublin: Sophis.

Dungey, M., McKenzie, M., and Tambakis, D. (2009), Flight-to-Quality and Asymmetric Volatility Responses in U.S. Treasuries. *Global Finance Journal* **19**(3), 252-267.

Easley, D. and O'Hara, M. (2005), Regulation and Return: The Role of Ambiguity. *Working Paper. Cornell University*.

Ederington, L. (1979), The Hedging Performance of the New Futures Markets. *Journal of Finance* **34**(1), 157-170.

Edison, H. (2003), Do Indicators of Financial Crises Work? An Evaluation of an Early Warning System. *International Journal of Finance and Economics* **8**(1), 11-53.

Eichengreen, B., Hale, G., and Mody, A. (2001), Flight-to-Quality: Investor Risk Tolerance and the Spread of Emerging Market Crises. In: Claessens, S. and Forbes, K., (Ed.) *International Financial Contagion*, pp. 129-155. Boston: Kluwer Academic Publishers.

Elton, E., Gruber, M., Brown, S., and Goetzmann, W. (2009), *Modern Portfolio Theory and Investment Analysis*. 8$^{th}$ edn, Hoboken, New Jersey: John Wiley and Sons.

Ennis, H. and Keister, T. (2006), Bank Runs and Investment Decisions Revisited. *Journal of Monetary Economics* **53**, 217-232.

Estrada, M. (2009), Alerting or Forecasting Economic Crisis? *Working Paper 10. Faculty of Economics and Administration, University of Malaya*.

European Central Bank (2007), Measuring Investors' Risk Appetite. *ECB Financial Stability Review*, June, 166-171.

Fabozzi, F. (2008), *The Handbook of Fixed Income Securities*. 7$^{th}$ edn, New York: McGraw-Hill.

Fair, R. (2009), Using a Macroeconometric Model to Analyze the 2008–2009 Recession and Thoughts on Macroeconomic Forecastability. *Working Paper. Cowles Foundation and International Center for Finance, Yale University*.

Fama, E. (1965), The Behavior of Stock Market Prices. *Journal of Business* **38**(1), 34–105.

Fama, E. and French, K. (1993), Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* **33**(1), 3-56.

Fama, E. and French, K. (1996), Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance* **51**(1), 55-84.

Faria, A., Mauro, P., and Zaklan, A. (2011), The External Financing of Emerging Markets - Evidence from Two Waves of Financial Globalization. *Review of Finance* **15**(1), 207-243.

Fauvel, Y., Paquet, A., and Zimmerman C. (1999), A Survey on Interest Rate Forecasting. *Working paper 87. Center for Research on Economic Fluctuations and Employment*.

Fink, J., Fink, K., and Lange, S. (2005), The Use of Term Structure Information in the Hedging of Mortgage-Backed Securities. *Journal of Futures Markets* **25**(7), 661–678.

Fischhoff, B., Slovic, P., and Lichtenstein S. (1977), Knowing with Certainty: the Appropriateness of Extreme Confidence. *Journal of Experimental Psychology: Human Perception and Performance* **3**(4), 552-564.

Fishburn, P. (1977), Mean-Risk Analysis With Risk Associated With Below-Target Returns. *American Economic Review* **67**(2), 116-126.

Fisher, L. and Weil, R. (1971), Coping With the Risk of Market-Rate Fluctuations: Returns to Bondholders from Naïve and Optimal Strategies. *Journal of Business* **44**(4), 408-431.

Flavin, T. and Panopoulou, E. (2009), On the Robustness of International Portfolio Diversification Benefits to Regime-Switching Volatility. *Journal of International Financial Markets, Institutions and Money* **19**(1), 140-156.

Flood, R. and Garber, P. (1984), Collapsing Exchange Rate Regimes: Some Linear Examples. *Journal of International Economics* **17**, 1-13.

Fong, G. and Vasicek, O. (1983), Return Maximization for Immunized Portfolios In: Kaufman, G., Bierwag, G., and Toevs, A., (Ed.) *Bond Portfolio Management: Duration Analysis and Immunization*, pp. 227-238. Greenwich: JAI Press.

Fong, G. and Vasicek, O. (1984), A Risk Minimization Strategy for Portfolio Immunization. *Journal of Finance* **39**, 1541–1546.

Forbes, K. (2002), Are Trade Linkages Important Determinants of Country Vulnerability to Crises? In: Edwards, S. and Frankel, J., (Ed.) *Preventing Currency Crises in Emerging Markets*, pp. 77-124. Chicago: University of Chicago Press.

Forbes, K. (2004), The Asian Flu and Russian Virus: The International Transmission of Crises in Firm-Level Data. *Journal of International Economics* **63**(1), 59-92.

Forbes, K. and Rigobon, R. (2002), No Contagion, Only Independence: Measuring Stock Market Co-Movements. *The Journal of Finance* **57**(5), 2223-2261.

Fostel, A. and Geanakoplos, J. (2008), Leverage Cycles and the Anxious Economy. *American Economic Review* **98**(4), 1211-1244.

Fourcans, A. and Franck, R. (2004), *Currency Crises: A Theoretical and Empirical Perspective*. Cheltenham: Edward Elgar Pub.

Frankel, J. and Saravelos, G. (2010), Are Leading Indicators of Financial Crises Useful for Assessing Country Vulnerability? Evidence from the 2008-09 Global Crises. *Working Paper w16047. National Bureau of Economic Research.*

Freixas, X. and Holthausen, C. (2005), Interbank Market Integration under Asymmetric Information. *Review of Financial Studies* **18**(2), 459-490.

Friedman, M. and Schwartz, A. (1963), *A Monetary History of the United States, 1867-1960*. Princeton: Princeton University Press.

Fromlet, H. (2001), Behavioral Finance – Theory and Practical Applications. *Business Economics* **36**(3), 63-69.

Froot, K. and Dabora E. (1999), How are Stock Prices Affected by the Location of Trade? *Journal of Financial Economics* **53**(2), 189-216.

Gai, P. and Vause, N. (2005), Measuring Investors' Risk Appetite. *Working Paper 283, Bank of England*.

Gameiro, I. and Sousa, J. (2010), Monetary Policy Effects: Evidence from the Portuguese Flow of Funds. *Working Paper 14. Banco de Portugal*.

Gatev, E. and Strahan, P. (2006), Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market. *The Journal of Finance* **61**(2), 867-892.

Gay, G. and Kolb, R. (1983), Interest Rate Futures: A New Perspective on Immunization. *Journal of Portfolio Management* **10**, 65-70.

Germanier, B. (2003), Updated Risk Index. *UBS: Foreign Exchange Note*, *September.*

Gertler, M. and Gilchrist, S. (1993), The Role of Credit Market Imperfections in the Monetary Transmission Mechanism: Arguments and Evidence. *Scandinavian Journal of Economics* **95**(1), 43-64.

Giannone, D., Lenza, M., and Reichlin, L. (2010), Market Freedom and the Global Recession. *Working Paper 288. European Corporate Governance Institute*.

Girault, A. (2010), *Emerging Market Debt: Where to Next?* London: Aviva Investors Global Services Ltd.

Glick, R. and Rose, A. (1999), Contagion and Trade: Why are Currency Crises Regional? *Journal of International Money and Finance* **18**, 603-17.

Goldstein, I. and Pauzner, A. (2005), Demand Deposit Contracts and the Probability of Bank Runs. *Journal of Finance* **60**(3), 1293-1327.

Gonzalo, J. and Olmo, J. (2005), Contagion versus Flight-to-Quality in Financial Markets. *Working Paper 05-18. Universidad Carlos III Madrid*.

Gorton, G. (1988), Banking Panics and Business Cycles. *Oxford Economic Papers* **40**(4), 751-781.

Gorton, G. (2009), Information, Liquidity, and the (Ongoing) Panic of 2007. *American Economic Review* **99**(2), 567-572.

Gorton, G. and He, P. (2008), Bank Credit Cycles. *Review of Economic Studies* **75**(4), 1181-1214.

Gorton, G. and Huang, L. (2004), Liquidity, Efficiency, and Bank Bailouts. *American Economic Review* **94**(3), 455-483.

Goyenko, R. and Sarkissian, S. (2009), Flight-to-Liquidity and Global Equity Returns. *American Finance Association San Francisco Meetings Paper*.

Goyenko, R. and Ukhov, A. (2009), Stock and Bond Market Liquidity: A Long-Run Empirical Analysis. *Journal of Financial and Quantitative Analysis* **44**(1), 189-212.

Graham, J. and Harvey, C. (2001), The Theory and Practice of Corporate Finance: Evidence from the Field. *Journal of Financial Economics* **60**(2-3), 187-243.

Green, E. and Lin, P. (2000) Diamond and Dybvig's Classical Theory of Financial Intermediation: What's Missing?" *Federal Reserve Bank of Minneapolis Quarterly Review* **24**, 3-13.

Grewal, M. and Angu, A. (2001), *Kalman Filtering: Theory and Practice using MATLAB*. 2nd edn, New York: John Wiley & Sons.

Groot, S. (1998), *Behavioral Aspects of Decision Models in Asset Management*. The Netherlands: Labyrint Publications.

Gubareva, M. (2010), *Flight-to-Quality Analysis for Financial Stability Enhancements*. In: Prachlias, C., (Ed.) Proceedings of the 7th International Conference on Applied Financial Economics, pp. 270-279. Greece: National and Kapodistrian University of Athens.

Gulko, L. (2002), Decoupling. *Journal of Portfolio Management* **28**(3), 59–66.

Gupta, A. and Subrahmanyam, M. (2005), Pricing and Hedging Interest Rate Options: Evidence from Cap–Floor Markets. *Journal of Banking and Finance* **29**, 701–733.

Hair, I., Anderson, R., and Tatham, R. (1990), *Multivariate Data Analysis with Readings*. 2nd edn, New York: Macmillan Publishing Co.

Harlow, W. (1991), Asset Allocation In A Downside-Risk Framework. *Financial Analyst Journal* **47**(5), 28-40.

Harris, L. and Gurel, E. (1986), Price and Volume Effects Associated with Changes in the S&P 500: New Evidence for the Existence of Price Pressure. *Journal of Finance* **41**, 851-860.

Harrison, M. and Kreps, D. (1979), Martingales and Arbitrage in Multiperiod Security Markets. *Journal of Economic Theory* **20**(3), 381-408.

Harrison, M. and Pliska, S. (1981), Martingales and Stochastic Integrals in the Theory of Continuous Trading. *Stochastic Processes and their Applications* **11**(3), 215–260.

Hartmann, P., Straetmans, S., and Devries, C. (2004), Asset Market Linkages in Crisis Periods. *The Review of Economics and Statistics* **86**(1), 313-326.

Haslem, J., Scheraga, C., and Bedingfield, J. (1992), An Analysis of the Foreign and Domestic Balance Sheet Strategies of the U.S. Banks and Their Association to Profitability Performance. *Management International Review* **32**(1), 55-75.

Hawley, F. (1907), *Enterprise and the productive process.* New York and London: The Knickerboocker Press.

He, Z. and Xiong, W. (2009), Dynamic Bank Runs. *Working paper. University of Chicago.*

He, Z. and Krishnamurthy, A. (2008), Intermediary Asset Pricing. *Working Paper 14517. The National Bureau of Economic Research*.

He, Z. and Krishnamurthy, A. (2009), A Model of Capital and Crises. *Working Paper. Northwestern University.*

Heath, D., Jarrow, R., and Morton, A. (1992), Bond Pricing and the Term Structure of Interest Rates: A New Methodology for Contingent Claims Valuation. *Econometrica* **60**(1), 77-105.

Hellwig, M. (1994), Liquidity provision, Banking, and the Allocation of Interest Rate Risk. *European Economic Review* **38**(7), 1363-1389.

Hicks, J. (1935), A Suggestion for Simplifying the Theory of Money. *Economica, New Series* **2**(5), 1-19.

Hicks, J. (1939), *Value and Capital*. Oxford: Clarendon Press.

Hirshleifer, D. (2001), Investor Psychology and Asset Pricing. *Journal of Finance* **56**, 1533-1597.

Ho, S. and Lee, S. (2004), *The Oxford Guide to Financial Modeling*. Oxford: Oxford University Press.

Ho, T. (1992), Key Rate Durations: Measures of Interest Rate Risks. *Journal of Fixed Income* **2**(2), 29-44.

Hoggarth, G., Saporta, V., and Reis, R. (2002), Costs of Banking System Instability: Some Empirical Evidence. *Journal of Banking and Finance* **26**(5), 825-855.

Holmstrom, B. and Tirole, J. (1997), Financial Intermediation, Loanable Funds and the Real Sector. *Quarterly Journal of Economics* **112**(3), 663-691.

Hong, H., Scheinkman, J., and Xiong, W. (2008), Advisors and Asset prices: A Model of the Origins of Bubbles. *Journal of Financial Economics* **89**(2), 268-287.

Hull, J. (2008), *Options, Futures, and Other Derivatives*. 7$^{th}$ edn, New Jersey: Prentice Hall.

Illing, M. and Aaron, M. (2005), A Brief Survey of Risk-Appetite Indexes. *Bank of Canada Financial System Review June*, 37–43.

Inci, A., Li, H., and McCarthy, J. (2011), Measuring Flight-to-Quality: a Local Correlation Analysis. *Review of Accounting and Finance* **10**(1), 69-87.

Ingersoll, J., Skelton, J., and Weil, R. (1978), Duration Forty Years Later. *Journal of Financial and Quantitative Analysis* **13**(4), 621-50.

International Monetary Fund (2011), *World Economic Outlook: Slowing Growth, Rising Risks*. Washington.

Jacklin, C. and Bhattacharya, S. (1988), Distinguishing Panics and Information-Based Bank Runs: Welfare and Policy Implications. *Journal of Political Economy* **96**(3), 568-592.

Jarrow, R., Protter, P., and Shimbo, K. (2010), Asset Price Bubbles in Incomplete Markets. *Mathematical Finance* **20**, 145-185.

Jeanneret, A. (2009), The Dynamics of Sovereign Credit Risk. *Working Paper. Swiss Finance Institute*.

Jo, H., Han, I., and Lee, H. (1997), Bankruptcy Prediction Using Case-Based Reasoning, Neural Network and Discriminant Analysis for Bankruptcy Prediction. *Expert Systems with Applications* **13**(2), 97-108.

Johansen, A. and Sornette, D. (1999), Modeling the Stock Market Prior to Large Crashes. *The European Physical Journal* **B**, 167–174.

Johansen, A. and Sornette, D. (2001), Bubbles and Anti-Bubbles in Latin-American, Asian and Western Stock Markets: An Empirical Study. *International Journal of Theoretical and Applied Finance* **4**(6), 853-920.

Kahneman, D. and Tversky, A. (1979), Prospect Theory: An Analysis of Decision Under Risk. *Econometrica* **47**(2), 263-291.

Kamin, S. and Kleist, K. (1999), The Evolution and Determinants of Emerging Market Credit Spreads in the 1990s. *Working Paper 68. Bank for International Settlements*.

Kaminsky, G. and Reinhart, C. (1999), The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review* **89**(3), 473-500.

Kaminsky, G., Lizondo, S., and Reinhart, C. (1998), Leading Indicators of Currency Crises. *Working Paper 97/79. International Monetary Fund.*

Karels, G and Prakash, A. (1987), Multivariate Normality and Forecasting of Business Bankruptcy. *Journal of Business Finance and Accounting* **14**(4), 573-593.

Keynes, J. (1936), *The General Theory of Employment, Interest and Money*. Cambridge: Macmillan Cambridge University Press.

Kindleberger, C. (1978), *Manias, Panics, and Crashes: A History of Financial Crises*. New York: Basic Books.

Knight, F. (1921), *Risk, Uncertainty, and Profit*. Boston MA: Hart, Schaffner and Marx; Houghton Mifflin.

Kolari, J., Glennon, D., Shin, H., and Caputo. M. (2002), Predicting Large US Commercial Bank Failures. *Journal of Economics and Business* **54**(4), 361-387.

Kolb, R. and Chiang, R. (1981), Improving Hedging Performance Using Interest Rate Futures. *Financial Management* **10**(4), 72–79.

Kolb, R. and Chiang, R. (1982), Duration, Immunization, and Hedging with Interest Rate Futures. *Journal of Financial Research* **5**(2), 161-170.

Kolb, R. and Overdahl, J. (2006), *Understanding Futures Markets*. 6th edn, New Jersey: Wiley-Blackwell.

Kolb, R. and Overdahl, J. (2007), *Futures, Options, and Swaps*. 5th edn, Oxford: Blackwell Publishing.

Kolodner, J. (1993), *Case-Based Reasoning*. San Francisco: Morgan Kaufmann Publishers Inc.

Kouri, P. (1976), The Exchange Rate and the Balance of Payments in the Short Run un the Long Run: a Monetary Approach. *Scandinavian Journal of Economics* **78**(4), 280-304.

Koutmos, G. and Pericli, A. (1999), Hedging GNMA Mortgage-Backed Securities with T-Note Futures: Dynamic versus Static Hedging. *Real Estate Economics* **27**(2), 335-363.

Krishnamurthy, A. (2002), The Bond/Old-Bond Spread. *Journal of Financial Economics* **66**(2), 463-506.

Krishnamurthy, A. (2010), Amplification Mechanisms in Liquidity Crises. *American Economic Journal: Macroeconomics* **2**(3), 1-30.

Krugman, P. (1979), A Model of Balance of Payments Crises. *Journal of Money, Credit, and Banking* **11**(3), 311-325.

Krugman, P. (2000), *Currency Crises*. The National Bureau of Economic Research Conference Report, Chicago: The University of Chicago Press.

Kumar, M. and Persaud, A. (2002), Pure Contagion and Investors' Shifting Risk Appetite: Analytical Issues and Empirical Evidence. *International Finance* **5**(3), 401-436.

Kumar, M., Moorthy, U., and Perraudin, W., (2003), Predicting Emerging Market Currency Crashes. *Journal of Empirical Finance* **10**(4), 427-454.

Kumar, P. and Ravi, V. (2007), Bankruptcy Prediction in Banks and Firms via Statistical and Intelligent Techniques – A Review. *European Journal of Operational Research* **180**(1), 1-28.

Kuo, I., Lin, Y., and Chang, Y. (2007), Which Interest Rate Option Model? *International Research Journal of Finance and Economics* **10**, 65-75.

Lamont, O. and Thaler, R. (2003), Can the Market add and Subtract? Mispricing in Tech Stock Carve-Outs. *Journal of Political Economy* **111**(2), 227−268.

Lane, W., Looney, S., and Wansley, J. (1986), An Application of the Cox Proportional Hazards Model to Bank Failure. *Journal of Banking and Finance* **10**, 511-531.

Lang, W. and Nakamura, L. (1995), Flight-to-quality in Banking and Economic Activity. *Journal of Monetary Economics* **36**, 145-164.

Lavington, F. (1921), *The English Capital Market*. London: Methuen.

Lee, S. (2011), Emerging Markets Debt: An Evolving Opportunity Set. *Morgan Stanley Smith Barney LLC: Consulting Group Investment Advisor Research* **14**(7), 1-13.

Lei, Q. (2009), Flight to Liquidity due to Heterogeneity in Investment Horizon. *Working paper. Cox School of Business, Southern Methodist University*.

Leibowitz, M. (1986a), The Dedicated Bond Portfolio in Pension Funds - Part I: Motivations and Basics. *Financial Analysts Journal* **42**(1), 68-75.

Leibowitz, M. (1986b), The Dedicated Bond Portfolio in Pension Funds - Part II: Immunization, Horizon Matching and Contingent Procedures. *Financial Analysts Journal* **42**(2), 47-57.

Leland, H. (1985), Option Pricing and Replication with Transaction Costs. *Journal of Finance* **11**(5), 1283-1301.

Lesne, A. (2010), *Hedging Interest Rate Risk to Protect Corporate Bond Returns*. Boston: State Street Corporation.

Levy, H. and Markowitz, H. (1979), Approximating Expected Utility by a Function of Mean and Variance. *American Economic Review* **69**(3), 308-317.

Lin, C., Khan, H., Chang, R., and Wang, Y. (2008), A New Approach to Modeling Early Warning Systems For Currency Crises: Can a Machine-Learning Fuzzy Expert

System Predict the Currency Crises Effectively? *Journal of International Money and Finance* **27**(7), 1098-1121.

Lin, P. and Chen, J. (2008), A Genetic-Based Hybrid Approach to Corporate Failure Prediction. *International Journal of Electronic Finance* **2**(2), 241-255.

Lintner, J. (1965), The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review in Economics and Statistics* **47**, 13-37.

Longstaff, F. (2004), The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices. *The Journal of Business* **77**(3), 511-526.

Loser, C. (2009), Global Financial Turmoil and Emerging Market Economies: Major Contagion and a Shocking Loss of Wealth? *Global Journal of Emerging Market* **1**(2), 137-158.

Lucas, R. (1978), Asset Prices in an Exchange Economy. *Econometrica* **46**(6), 1429–1445.

Ma, W., Morita, G., and Detko, K. (2008), Re-Examining the Hidden Costs of the Stop-Loss. *Working Paper. University of Washington*.

Macaulay, F. (1938), *Some Theoretical Problems Suggested by the Movements of Interest Rates Bond Yields and Stock Prices in the U.S since 1856*. New York: Columbia University Press for the National Bureau of Economic Research.

Makarov, I. and Plantin, G. (2012), Equilibrium Subprime Lending. *Journal of Finance,* Forthcoming.

Makridakis, S., Hogarth, R., and Gaba, A. (2009), Forecasting and Uncertainty in the Economic and Business World. *International Journal of Forecasting* **25**(4), 794-812.

Mandelbrot, B. (1963), The Variation of Certain Speculative Prices. *Journal of Business* **36**(4), 394–419.

Mandelbrot, B. and Hudson, R. (2004), *The (Mis) Behavior of Markets*. London: Profile.

Mao, J. (1970), Models Of Capital Budgeting, E-V vs. E-S. *Journal of Financial and Quantitative Analysis* **5**(5), 657-676.

Markowitz, H. (1952), Portfolio Selection. *The Journal of Finance* **7**(1), 77-91.

Markowitz, H. (1956), The Optimization of a Quadratic Function Subject to Linear Constraints. *Naval Research Logistics Quarterly* **3**(1-2), 111-133.

Markowitz, H. (1959), *Portfolio Selection: Efficient Diversifications of Investments*. Cowles Foundation Monograph № 16. New York: John Wiley & Sons, Inc.

Markowitz, H. (1992), Foundation of Portfolio Theory. In: Maler, K., (Ed.) *Nobel Lectures in Economic Science (1981-1990)*, pp. 279-287. Singapore, New Jersey, London, Hong Kong: World Scientific.

Martellini, L., Priaulet, P., and Priaulet, S. (2003), *Fixed Income Securities: Valuation, Risk Management, and Portfolio Strategies*. Chichester: John Wiley & Sons Ltd.

Martin, D. (1977), Early Warning of Bank Failure: A Logit Regression Approach. *Journal of Banking and Finance* **1**, 249-276.

Maslov, V. (2003), Approximation Probabilities, the Law of a Quasi-stable Market, and a Phase Transition from the"Condensate" State. *Doklady Mathematics* **68**(2), 266-270.

Maslov, V. (2004), Zeroth-Order Phase Transitions. *Mat. Zametki* **76**(5), 748–761.

Maslov, V. (2005), Connection of Quasistable Economics with Thermodynamics of Superfluid Liquid. Default as the Phase Transition to the Zero Kind. *OP&PM Surveys in Applied and Industrial Mathematics* **12**(1), 3-40. (Russian language edition)

Maslov, V. (2008), Economic Law of Increase of Kolmogorov Complexity. Transition from Financial Crisis 2008 to the Zero-Order Phase Transition (Social Explosion). *Quantitative Finance Papers* available at www.arxiv.org.

Masson, P. (1999), Contagion: Macroeconomic Models with Multiple Equilibria. *Journal of International Money and Finance* **18**(4), 587-602.

McKee, T. (2000), Developing a Bankruptcy Prediction Model via Rough Sets Theory. *International Journal of Intelligent Systems in Accounting, Finance and Management* **9**(3), 159-173.

McKenzie, D. and Maslakovic, M. (2010), *External Finance for Emerging Markets 2010*. London: International Financial Services London.

Meindl, P. (2007), Portfolio Optimization and Dynamic Hedging with Receding Horizon Control, Stochastic Programming, and Monte Carlo Simulation. *Ph.D. Thesis: Department of Management Science and Engineering, Stanford University*.

Merton R. (1974), On the Pricing of Corporate Debt: the Risk Structure of Interest Rates. *Journal of Finance* **29**(2), 449-70.

Merton, R. (1973), Theory of Rational Option Pricing. *Bell Journal of Economics and Management Science* **4**(1), 141-183.

Mishkin, F. (1992), Anatomy of a Financial Crisis. *Journal of Evolutionary Economics* **2**(2), 115-130.

Mishkin, F. (2009), Is Monetary Policy Effective during Financial Crises? *American Economic Review* **99**(2), 573-77.

Misina, M. (2005), Risk Perceptions and Attitudes. *Working Papers 2005-17. Bank of Canada.*

Misina, M. (2006), Benchmark Index of Risk Appetite. *Working Paper 2006-16. Bank of Canada*.

Mitchell, W. (1941), *Business Cycles and Their Causes*. Berkeley: University of California Press.

Mitzenmacher, M. (2004), A Brief History of Generative Models for Power Law and Lognormal Distributions. *Internet Mathematics* **1**(2), 226-251.

Molina, C. (2002), Predicting Bank Failures Using a Hazard Model: the Venezuelan Banking Crisis. *Emerging Market Review* **3**(1), 31-50.

Morgan, G. (1986), Floating Rate Securities and Immunization: Some Further Results. *The Journal of Financial and Quantitative Analysis* **21**(1), 87- 94.

Morris, S. and Shin, H. (2001), Rethinking Multiple Equilibria in Macroeconomic Modeling. In: Bernanke, B. and Rogoff, K., (Ed.), *NBER Macroeconomics Annual*, pp. 139-182. Cambridge: MIT Press.

Morrison, A. and White, L. (2005), Crises and Capital Requirements in Banking. *American Economic Review* **95**(5), 1548-1572.

Mossin, J. (1966), Equilibrium in a Capital Market. *Econometrica* **34**(4), 768-783.

Nachev, A. and Hill, S. (2010), Adaptive Resonance Theory Applications for Business Forecasting. In: Zhu, J. and Fung, G., (Ed.), *Forecasting Models: Methods and Applications*, pp. 97-108. Sunnybank Hills: iConcept Press.

Naes, R., Skjeltorp, J., and Odegaard, B. (2011), Stock Market Liquidity and the Business Cycle. *Journal of Finance* **66**(1), 139-176.

Nawalkha, S. and Chambers, D. (1996), An Improved Immunization Strategy: M-Absolute. *Financial Analysts Journal* **52**(5), 69-76.

Nawalkha, S. and Chambers, D. (1997), The M-Vector Model: Derivation and Testing of Extensions to the M-Square Model. *Journal of Portfolio Management* **23**(2), 92–98.

Nawalkha, S. and Soto, G. (2009), Managing Interest Rate Risk: The Next Challenge? *Journal of Investment and Management* **7**(3), 1–15.

Nawalkha, S., Soto, G., and Beliaeva, N. (2005), *Interest Rate Risk Modeling: The Fixed Income Valuation Course*. New Jersey: Wiley Finance, JohnWiley and Sons.

Nawalkha, S., Soto, G., and Zhang, J. (2003), Generalized M-Vector Models for Hedging Interest Rate Risk. *Journal of Banking and Finance* **27**(8), 1581–1604.

Nawrocki, D. (1991), Optimal Algorithms and Lower Partial Moment: Ex Post Results. *Applied Economics* **23**(3), 465-470.

Nawrocki, D. (1992), The Characteristics Of Portfolios Selected By n-Degree Lower Partial Moment. *International Review of Financial Analysis* **1**(3), 195-210.

Nelson, C. and Siegel, A. (1987), Parsimonious Modeling of Yield Curves. *Journal of Business* **60**(4), 473-489.

Newman, M. (2005), Power Laws, Pareto Distributions and Zipf's Law. *Contemporary Physics* **46**(5), 323–351.

Neziri H. (2009), Can Credit Default Swaps Predict Financial Crises? Empirical Study On Emerging Markets. *Journal of Applied Economic Sciences* **4**(1), 125-136.

Obstfeld M. (1986), Rational and Self-Fulfilling Balance of Payments Crises. *The American Economic Review* **76**(1), 72-81.

Obstfeld, M. (1994), Risk-Taking, Global Diversification, and Growth. *The American Economic Review* **84**(5), 1310-1329.

Obstfeld, M. (1996), Models of Currency Crises with Self-Fulfilling Features. *European Economic Review* **40**(3-5), 1037-1047.

Ogden, J. (1987), An Analysis of Yield Curve Notes. *The Journal of Finance* **42**(1), 99-110.

Olsen, R. (1998), Behavioral Finance and Its Implications for Stock-Price Volatility. *Financial Analysts Journal* **54**(2), 10-18.

Olson, D. and Charles, M. (2003), Neural Network Forecasts of Canadian Stock Returns Using Accounting Ratios. *International Journal of Forecasting* **19**(3), 453-465.

Ortiz, C., Stone, C., and Zissu, A. (2008), Delta Hedging of Mortgage-Servicing Portfolios under Gamma Constraints. *Journal of Risk Finance* **9**(4), 379 – 390.

Ortiz, C., Stone, C., and Zissu, A. (2009), Delta Hedging a Multi-Fixed-Income-Securities Portfolio under Gamma and Vega Constraints. *Journal of Risk Finance* **10**(2), 169-178.

Papageorgiou, N. and Skinner, F. (2002), Predicting the Direction of Interest Rate Movements. *The Journal of Fixed Income* **11**(4), 87-95.

Pareto, V. (1897), *Cours d'Economique Politique*. London: Macmillan.

Park, C. and Han, I. (2002), A Case-Based Reasoning with the Feature Weights Derived by Analytic Hierarchy Process for Bankruptcy Prediction. *Expert Systems with Applications* **23**(3), 255-264.

Park, S. and Jey, S. (2010), Estimation and Hedging Effectiveness of Time-Varying Hedge Ratio: Flexible Bivariate GARCH Approaches. *The Journal of Futures Markets* **30**(1), 71–99.

Pawlak, Z. (1982), Rough sets. *International Journal of Computer and Information Science* **11**(5), 341-356.

Peltonen, T. (2006), Are Emerging Market Currency Crises Predictable? *Working Paper 571. European Central Bank*.

Pettis, M. (2001), *The Volatility Machine*. Oxford: Oxford University Press.

Philippatos, G. (1971), Computer Programs for Implementing Portfolio Theory. *Unpublished Software, Pennsylvania State University*.

Plerou, V., Gopikrishnan, P., and Stanley, E. (2003), Two-Phase Behavior of Financial Markets. *Nature* **421**, 130.

Porter, R. (1974), Semi-variance And Stochastic Dominance: A Comparison. *American Economic Review* **64**(1), 200-204.

Porter, R. and Bey, R. (1974), An Evaluation Of The Empirical Significance Of Optimal Seeking Algorithms In Portfolio Selection. *Journal of Finance* **29**(5), 1479-1490.

Porter, R., Wart, J., and Ferguson, D. (1973), Efficient Algorithms For Conducting Stochastic Dominance Tests On Large Numbers Of Portfolios. *Journal of Financial and Quantitative Analysis* **8**(1), 71-81.

Pratt, W. (1964). Risk Aversion in the Small and in the Large. *Econometrica* **32**(1/2), 122–136.

Quirk, J. and Saposnik, R. (1962), Admissibility and Measurable Utility Functions. *Review of Economic Studies* **29**, 140-146.

Redington, F. (1952), Review of the Principle of Life Office Valuations. *Journal of the Institute of Actuaries* **78**(3), 286-340.

Reilly, F. and Brown, K. (2008), *Investment Analysis and Portfolio Management*. 9th edn, Cincinnati, Ohio: South-Western College Pub.

Repullo, R. and Suarez, J. (2008), The Procyclical Effects of Basel II. *Discussion Paper 6862*. *Centre for Economic Policy Research.*

Repullo, R. and Suarez, J. (2010), The Procyclical Effects of Bank Capital Regulation. *Discussion Paper 29S. Tilburg University, Center for Economic Research.*

Ritter, J. (2003), Behavioral Finance. *Pacific-Basin Finance Journal* **11**(4), 429-437.

Robertson, D. (1928), *Money*. 2nd edn, Cambridge: Cambridge University Press.

Rom, B. and Ferguson K. (1997/1998), Using Post-Modern Portfolio Theory to Improve Investment Performance Measurement. *Journal of Performance Measurement* **2**(2), 5-13.

Rom, B. and Ferguson, K. (1994), Portfolio Theory Is Alive And Well: A Response. *Journal of Investing* **3**(3), 24-44.

Rosenberg, D. (2003), Introducing Merrill Lynch's Proprietary Weekly Indicators. *Merrill Lynch: The Market*, *June*, 4–10.

Rosenberg, M. (2008), *Financial Conditions Watch, Global Financial Market Trends and Policy*. Bloomberg LLP.

Rosenberg, M. (2009), *Financial Conditions Watch, Global Financial Market Trends and Policy*. Bloomberg LLP.

Ross, C. and Bernal, A. (2007), *Commentary across the Grades: Emerging Markets Sovereigns*. New York: Bear, Stearns & Co. Inc.

Ross, S. (1976), Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory* **13**(3), 341-360.

Rossi, E. and Zuca, C. (2002), Hedging Interest Rate Risk with Multivariate GARCH. *Applied Financial Economics* **12**(4), 241 – 251.

Routledge, B. and Zin, S. (2009), Model Uncertainty and Liquidity. *Review of Economic Dynamics* **12**(4), 543-566.

Roy, A. (1952), Safety First and the Holding of Assets. *Econometrica* **20**(3), 431-449.

Sach J. (1986), The Bolivian Hyperinflation and Stabilization. *Working paper. National Bureau of Economic Research*.

Sachs, J. (1984), Theoretical Issues in International Borrowing. *Princeton Studies in International Finance* **54**. Princeton, N.J.: Princeton University Press.

Sachs, J., Tornell, A., and Velasco, A. (1996), Financial Crises in Emerging Markets: The Lessons from 1995. *Working Paper W5576. National Bureau of Economic Research*.

Samartin, M. (2003), On the Optimality of Bank Runs: Comment on Allen and Gale. *The Geneva Papers on Risk and Insurance Theory* **28**(1), 33-57.

Samuelson, P. (1958), An Exact Consumption-Loan Model of Interest with or without the Social Contrivance of Money. *The Journal of Political Economy* **66**(6), 467-482.

Samuelson. P. (1945), The Effect of Interest Rate Increases on the Banking System. *American Economic Review* **35**(1), 16-27.

Savage, L. (1954), *The Foundations of Statistics*. New York: John Wiley & Sons, Inc.

Scalas, E. (2006), The Application of Continuous-Time Random Walks in Finance and Economics. *Physica A* **362**, 225–239.

Scheinkman, J. and Xiong, W. (2003), Overconfidence and Speculative Bubbles. *Journal of Political Economy* **111**(6), 1183-1219.

Sharpe, W. (1963), A Simplifies Model of Portfolio Analysis. *Management Science* **9**(2), 277-293.

Sharpe, W. (1964), Capital Asset Prices. A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance* **19**(3), 425-442.

Sharpe, W. (1966), Mutual Fund Performance. *Journal of Business* **39**(1), 119–138.

Sharpe, W. (1994), The Sharpe Ratio. *Journal of Portfolio Management* **21**(1), 49–58.

Sharpe, W. (1995), Risk, Market Sensitivity and Diversification. *Financial Analysis Journal* **51**(1), 84-88.

Shefrin, H. (2002), *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. Oxford: Oxford University Press.

Sheraz, A. (2006), Effectiveness of Time-Varying Hedge Ratio with Constant Conditional Correlation. Empirical Evidence from U.S. Treasury Market. *Working Paper. Department of Finance and Statistics, Hanken School of Economics*.

Shiller, R. (2005), *Irrational Exuberance*. 2nd edn, Princeton: Princeton University Press.

Shiller, R. and Akerlof, G. (2009), *Animal Spirits: How Human Psychology Drives the Economy And Why It Matters for Global Capitalism*. Princeton: Princeton University Press.

Shleifer, A. (1986), Do Demand Curves for Stocks Slope Down? *Journal of Finance* **41**(3), 579−590.

Shleifer, A. (2000), *Inefficient Markets: An Introduction to Behavioral Finance*. New York: Oxford University Press.

Shleifer, A. and Vishny, R. (1997), The Limits to Arbitrage. *Journal of Finance* **52**, 35-55.

Shumway, T. (2001), Forecasting Bankruptcy More Accurately: A Simple Hazard Model. *The Journal of Business* **74**(1), 101-124.

Singh, S. and McAtackney, P. (1998), *Dynamic Time-Series Forecasting using Local Approximation*. Proceedings of the 10th IEEE International Conference on Tools with Artificial Intelligence, pp. 392-399. Taiwan: IEEE Press.

Slowinski, R., Greco, S., and Matarazzo, B. (2005), Rough Set Based Decision Support. In: Burke, E. and Kendall, G., (Ed.) *Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques*, pp. 475-527. New York: Springer-Verlag.

Sornette, D. (2003), *Why Stock Markets Crash: Critical Events in Complex Financial Systems*. Princeton: Princeton University Press.

Sornette, D. and Johansen, A. (2001), Significance of Log-Periodic Precursors to Financial Crashes. *Quantitative Finance* **1**(4), 452-471.

Sornette, D., Johansen, A., and Bouchaud, J. (1996), Stock Market Crashes, Precursors and Replicas. *Journal de Physique I France* **6**(1), 167–175.

Sortino, F. (2001), From Alpha to Omega. In: Sortino, F. and Satchell, S., (Ed.) *Managing Downside Risk in Financial Markets: Theory, Practice and Implimentation*, pp. 3-25. Oxford: Reed Educational and Professional Publishing Ltd.

Sortino, F. and Meer, R. (1991), Downside Risk: Capturing What's at Stake. *Journal of Portfolio Management* **17**(4), 27-31.

Sortino, F. and Price, L. (1994), Performance Measurement in a Downside Risk Framework. *Journal of Investing* **3**(3), 59–65.

Sterling, W. (2009), Looking Back at Lehman: An Empirical Analysis of the Financial Shock and the Effectiveness of Countermeasures. *Musashi University Journal* **57**(2), 53-87.

Sullivan, K. and Kiggins, T. (1989), Convexity. The Name is New but You Always Knew What It Was. In: Fabozzi, F., (Ed.) *The Institutional Investor Focus on Investment Management*, pp. 214-239. Cambridge, MA: Ballinger.

Sveshnikov, S. and Bocharnikov, V. (2009), Forecasting Financial Indexes with Model of Composite Events Influence. *Journal of Applied Economic Sciences* **4**(3), 425-440.

Swicegood, P. and Clark, J. (2001), Off-site Monitoring Systems for Predicting Bank Underperformance: A Comparison of Neural Networks, Discriminant Analysis, and Professional Human Judgment. *International Journal of Intelligent Systems in Accounting, Finance and Management* **10**(3), 169-186.

Takayasu, H., Takayasu, M., Okazaki, M., Marumo, K., and Shimizu, T. (2000), Fractal Properties in Economic. In: Novak M., (Ed.) *Paradigms of Complexity*, pp. 243-257. Singapore: World Scientific.

Taleb, N. (2010), *The Black Swan: The Impact of the Highly Improbable*. 2nd edn, New York: Random House Publishing Group.

Tam, K. and Kiang, M. (1992), Predicting Bank Failures: A Neural Network Approach. *Decision Sciences* **23**, 926-947.

Taylor, J. (2009), *Getting Off Track: How Government Actions and Interventions Caused, Prolonged, and Worsened the Financial Crisis*. Stanford: Hoover Institution Press.

Thomas, M. and Mare, E. (2007), Long Term Forecasting and Hedging of the South African Yield Curve. *Paper presented at the Convention of the Actuarial Society of South Africa*.

Tirole, J. (1982), On the Possibility of Speculation under Rational Expectations. *Econometrica* **50**(5), 1163-1181.

Tirole, J. (1985), Asset Bubbles and Overlapping Generations. *Econometrica* **53**(6), 1499-1528.

Tobin, J. (1958), Liquidity Preference as Behavior towards Risk. *Review of Economic Studies* **25**(2), 65-86.

Tversky, A. and Kahneman, D. (1973), Availability: A Heuristic for Judging Frequency and Probability. *Cognitive Psychology* **5**(2), 207-232.

Tversky, A. and Kahneman, D. (1974), Judgment Under Uncertainty: Heuristics and Biases. *Science* **185**(4157), 1124-1131.

U.S. Department of the Treasury (2011), *Quarterly Release Data: 2011 - 4th Quarter*, Washington.

Van Rijckeghem, C. and Weder, B. (2001), Sources of Contagion: Is It Finance or Trade? *Journal of International Economics* **54**(2), 93-308.

Vance, M. and Dungey, M. (2007), Unravelling Financial Market Linkages during Crises. *Journal of Applied Econometrics* **22**(1), 89-119.

Vasicek O. (1984), *Credit Valuation*. San Francisco: KMV.

Vayanos, D. (2004), Flight-to-Quality, Flight-to-Liquidity, and the Pricing of Risk. *Working Paper 10327. National Bureau of Economic Research*.

Von Goetz, P. (2009), Asset Prices and Banking Distress: A Macroeconomic Approach. *Journal of Financial Stability* **5**(3), 298-319.

Von Neumann, J. and Morgenstern, O. (1944), *Theory of Games and Economic Behavior*. New Jersey: Princeton University Press.

Wallace, N. (1988), Another Attempt to Explain an Illiquid Banking System: The Diamond and Dybvig Model with Sequential Service Taken Seriously. *Federal Reserve Bank of Minneapolis Quarterly Review* **12**(4), 3-16.

Wallace, N. (1990), A Banking Model in Which Partial Suspension is Best. *Federal Reserve Bank of Minneapolis Quarterly Review* **14**(4), 11-23.

Wallas, G. (1960), Immunization. *Journal of the Institute of Actuaries Students' Societies* **15**, 345-357.

Walti, S. (2003), Testing for Contagion in International Financial Markets: Which Way to Go? *Working Paper 92. International Center for Financial Asset Management and Engineering.*

Walti, S. and Weder, G. (2009), Recovering from Bond Market Distress: Good luck and Good Policy. *Emerging Markets Review* **10**(1), 36-50.

Wang, P. (1999), Spectral Analysis of Economic Time Series Behaviour. *Working Paper 9914. Manchester School of Management*.

Watanabe, W. (2010), Does a Large Loss of Bank Capital Cause Evergreening? Evidence from Japan. *Journal of the Japanese and International Economies* **24**(1), 116-136.

Wijnbergen V. (1988), Inflation, Balance of Payments Crisis and Public Sector Deficits. In: Helpman, E., Razin, A., and Sadka E., (Ed.) *Economic Effects of the Government Budget*, pp.287-304. Cambridge: MIT Press.

World Bank (2010)*, Global Development Finance 2010: External Debt of Developing Countries*. Washington.

Wurgler, J. and Zhuravskaya K. (2002), Does Arbitrage Flatten Demand Curves for Stocks? *Journal of Business* **75**(4), 583−608.

Yawitz, J. (1989), Convexity: Introduction. In: Fabozzi, F., (Ed.) *The Institutional Investor Focus on Investment Management*, pp. 150-158. Cambridge: Ballinger.

Yegorov, Y. (2007), Econo-physics: A Perspective of Matching Two Sciences. *Evolutionary and Institutional Economic Review* **4**(1), 143-170.

Zanini, M. (2009), Power Curves: What Natural and Economic Disasters Have in Common. *The McKinsey Quarterly*, 1-5.

Zhao, H., Sinha, A., and Ge, W. (2009), Effects of Feature Construction on Classification Performance: An Empirical Study in Bank Failure Prediction. *Expert Systems with Applications* **36**(2), 2633-2644.

Zhou, W. and Sornette, D. (2009), A Case Study of Speculative Financial Bubble in the South African Stock Market 2003-2006. *Physica A* **388**(6), 869-880.